NEGOTIATIONS BETWEEN SELF-DRIVING VEHICLES AND PEDESTRIANS FOR THE RIGHT OF WAY AT UNMARKED INTERSECTIONS

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A thesis submitted in total fulfillment of the requirements for the degree of Doctor of Philosophy

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August 2019
The *harder* I work, the *luckier* I get.
— Samuel Goldwyn

Dedicated to the family
ABSTRACT

Negotiations among drivers and pedestrians are common on roads, but it is still challenging for a self-driving vehicle to negotiate for its right of way with other human road users, especially pedestrians. Currently, self-driving vehicles are expected to exhibit a conservative behavior by always yielding to the approaching pedestrians. This effect will slow down the future urban traffic significantly. In this thesis, a novel model of vehicle-pedestrian negotiation is proposed describing the processing and exchange of negotiation cues from both parties. The motion strategy for the vehicle approaching the pedestrian is formulated to negotiate its best chance to pass first. The research aims to reduce the conflict of interests between vehicles and pedestrians in typical traffic conditions, yet without compromising safety.

This research has been investigated in various stages. First, a preliminary review on formal traffic gestures is conducted to investigate the language of traffic. Then, negotiation concepts are established to demonstrate negotiations between a single vehicle and a single pedestrian based on physical constraints between them. The negotiation model is further extended by introducing fuzzy informal social rules for negotiations between groups of vehicles and pedestrians. The social rules are further studied, along with the risk-taking behaviors of pedestrians to extend the model to allow individual decision making among multiple vehicles and pedestrians. Lastly, the scalability of the model is validated by demonstrating multi-party negotiations. The possible negotiation opportunities for vehicles are modeled considering different risk-taking behaviors of pedestrians.

The model is implemented and tested in a micro-simulation traffic environment using SUMO and MATLAB. The behavior of individual vehicles and pedestrians are simulated along with an unmarked road network to test the impact on traffic flow. The simulation environments were defined to represent different complexities of traffic ranging from one-to-one vehicle-pedestrian interactions to multi-party vehicles-pedestrians’ interactions. In different traffic conditions, the simulation results show an overall improvement in the waiting time of vehicles and thus in the intersection throughput, compared to conservative vehicle behavior (up to 50% improvement in peak traffic conditions). The simulation results also show that the benefits of reduced waiting times for vehicles come at the cost of some waiting time for pedestrians. However, the observed pedestrian waiting times in this model are not longer than the generally accepted waiting times reported in empirical studies. The results however largely depend on pedestrians’ behaviors and situational factors. This research captures
those factors and different pedestrian behaviors while evaluating the research hypothesis. Despite, the results are subjected to a few simulation constraints, especially dealing with the uncertainty in estimation pedestrians’ intentions. Yet, this thesis is able to demonstrate possible directions for innovations in future human-vehicle interactions to maintain a smoother flow of traffic.

Ultimately, this research is able to demonstrate that negotiations in future can balance the right of way among vehicles and pedestrians, especially when the interaction happens at unregulated intersections. The concepts and concerns related to social behavior of self-driving vehicles presented in this research, along with the implications of this particular research, can further help in the future to improve the decision making of self-driving vehicles when they will be sharing the roads with humans.
DECLARATION

I confirm that:

1. this thesis and the work presented in it are my own, and comprises of the results of my own original research,

2. due acknowledgement has been made in the text where I have referred and consulted the work of others,

3. this thesis is fewer than 100,000 words in length as per university requirements which excludes tables, maps, bibliographies and appendices.

Surabhi Gupta
Melbourne, August 2019
Some ideas and figures have appeared previously in the following publications. In each case, I am the first author and researcher in charge; my co-authors have been my supervisors who contributed in guidance.


Other paper under review:


Also, the following non-reviewed magazine articles cover a summary of this thesis:


ACKNOWLEDGEMENTS

Before I embarked on my PhD journey, I knew that it would not be easy. And after going through multiple cycles of thinking, studying, working, writing and rewriting, finally I am writing this thesis - a proof of all my efforts in the last three years.

First, I would like to thank my supervisor, Prof Stephan Winter, for his guidance and support throughout this research. His critical evaluation of my research proposals along with the constructive feedback helped in shaping my research ideas and methodologies for my work. I express my sincere thanks to him for his quality supervision, knowledge sharing, availability, advice and guidance for my PhD research.

My sincere thanks also goes to Dr. Maria Vasardani, for her insightful comments at each stage of this research, and making me think about my research from different perspectives. I appreciate all her contributions in suggestions, reviews, and time, to make my research progress easy-going.

I would also like to thank Prof Bharat Lohani for inspiring my interest in the research and encouraging me to pursue doctoral study. Also, I appreciate and thank him for his guidance in my research as an external supervisor. I would also like to acknowledge Prof Allison Kealy for her initial discussions on this research, and Dr. Martin Tomko for managing my annual progress reviews as the committee chair of the advisory committee.

Also, I acknowledge and thank the Commonwealth Department of Education and Training Australia for supporting my research through the Australian Government Research Training Program Scholarship.

In addition, there are colleagues and friends, who were a happy distraction to rest my mind outside my research. I wish to thank Neeta, Namrata, Himanshu, and Sanjay for being my family away from home. There was also a social side of sharing and discussing ideas with a bunch of people in the office. My time at the university was enjoyable due to our ‘spatial’ group - Salil, Yaoli, Zahra, Michael, Rahul, Haifeng, Jelena, Ivan, Ehsan, Santa, David, Debjit, Subhra, Rajesh, and Masoud, who were of great support in fitting some fun into the busy work times. I would like to thank all of them for being such amazing colleagues. I also extend my thanks to Suwash, Ali, Sasan, and Kanishka who turned the shared lab space into a happy place to work.
Finally, I owe all my accomplishments to my parents, Harshendra and Rama Gupta, and my sister, Sugandha, and also to my extended family members, my parents-in-law. I sincerely thank them for their wise counsel, moral support, love, and encouragement, in all my pursuits. Last, but not the least, this journey would not have been that happier without the love and understanding of my husband, Himanshu, who made me feel cared and supported during the most stressful times. I am most proud of the blessings bestowed upon me in the form of my family. I will be eternally grateful to all these people who made it possible for me to arrive at the final destination of this journey.

Surabhi Gupta

Melbourne, August 2019
# CONTENTS

List of Figures xvi  
List of Tables xviii  
Acronyms xix  

1 INTRODUCTION  
1.1 Background and Motivation 3  
1.2 Challenges for a self-driving vehicle 5  
1.2.1 Interpreting language of traffic 5  
1.2.2 Intent perception and communication 5  
1.2.3 Social behavior 6  
1.2.4 Agreement in negotiation 6  
1.3 Research objectives and hypothesis 7  
1.4 Thesis contributions and outcomes 9  
1.5 Thesis structure 10  

2 LITERATURE REVIEW 13  
2.1 Socially acceptable vehicles 13  
2.1.1 Social behavior of self-driving vehicles 13  
2.1.2 Why is social interaction necessary? 14  
2.1.3 Theoretical reviews on safe vehicle design 16  
2.1.4 Studies on driver-pedestrian interactions 17  
2.1.5 Analysing interactions with self-driving vehicles 19  
2.2 Embedding social capabilities in future vehicles 20  
2.2.1 Social contexts in vehicle design 21  
2.2.2 Reviewing communication challenges 23  
2.2.3 Vehicle-to-Pedestrian (V2P) communication 25  
2.2.4 Other practical solutions - Smart roads 26  
2.3 Insights on pedestrians road-crossing behaviors 27  
2.3.1 Perception of safe gap 28  
2.3.2 Social information 29  
2.3.3 Interaction in groups 32  
2.3.4 Informal social rules 34  
2.3.5 Risk-taking behaviors 35  
2.4 Practical approaches to pedestrians detection and intention estimation 36  
2.4.1 Pedestrian detection 36  
2.4.2 Intention estimation methods 37  
2.4.3 Vision-based intention estimation methods 38  
2.4.4 Social contexts in intention estimation 40  
2.5 Conflict resolution by self-driving vehicles 40  
2.5.1 Cooperative behavior with connected vehicles 41  
2.5.2 Connected vehicles and pedestrians 42  

3 LANGUAGE OF INTERACTION IN TRAFFIC 45  
3.1 Gestural interaction in traffic 45
3.2 Universality of gestures - preliminary study .......... 46
  3.2.1 Research summary ................................ 46
  3.2.2 Psychology of gestures ............................. 47
  3.2.3 Approach ............................................ 47
  3.2.4 Traffic manual codes ................................ 48
  3.2.5 Evaluation ............................................ 50
3.3 Discussions ............................................. 52
3.4 Conclusions .............................................. 53

4 VEHICLE-PEDESTRIAN NEGOTIATION FRAMEWORK ....... 55
  4.1 Introduction ............................................ 55
  4.2 Negotiation framework .................................. 56
    4.2.1 What is negotiation? ............................... 56
    4.2.2 Conceptual model .................................. 57
    4.2.3 Vehicle-pedestrian interaction scenarios .......... 59
    4.2.4 Negotiation strategy ............................... 60
  4.3 Experiment design ....................................... 63
    4.3.1 Simulation environment ............................. 63
    4.3.2 Negotiation model .................................. 63
    4.3.3 Pedestrian behavior modeling ....................... 64
    4.3.4 Conservative vehicle model ......................... 65
    4.3.5 Observables .......................................... 65
  4.4 Results and Discussion ................................ 66
    4.4.1 Travel time analysis ............................... 66
    4.4.2 Time headway analysis ............................. 68
    4.4.3 Throughput analysis ............................... 70
  4.5 Conclusions ............................................. 74

5 INTRODUCING SOCIAL RULES IN NEGOTIATION .......... 77
  5.1 Introduction ............................................ 77
  5.2 Extended negotiation framework ......................... 78
    5.2.1 Elements of the negotiation model .................. 78
    5.2.2 Conceptual negotiation model ....................... 80
    5.2.3 Social rules formulation ........................... 81
    5.2.4 Negotiation criteria ............................... 83
    5.2.5 Negotiation examples ............................... 84
  5.3 Experiment design ....................................... 85
    5.3.1 Simulation environment ............................. 85
    5.3.2 Pedestrian modeling ................................ 85
    5.3.3 Experiment cases ................................... 86
    5.3.4 Observables ......................................... 87
  5.4 Results and Discussion ................................ 88
    5.4.1 Waiting time analysis ............................. 88
    5.4.2 Waiting group density analysis ..................... 92
    5.4.3 Throughput analysis ............................... 95
  5.5 Conclusions ............................................. 95

6 PEDESTRIAN’S RISK-BASED NEGOTIATIONS ............... 97
  6.1 Introduction ............................................ 97
6.2 Risk-based vehicle-pedestrian negotiation model . . . 98
  6.2.1 Pedestrian risk computation .......................... 99
  6.2.2 Pedestrian behavior ................................. 100
  6.2.3 Possible negotiation opportunities for vehicle . 101
  6.2.4 Conceptual negotiation model ....................... 102
  6.2.5 Example scenario .................................. 104
6.3 Experiment design ................................... 106
  6.3.1 Interaction environment .............................. 107
  6.3.2 Negotiation model .................................. 107
  6.3.3 Base model for comparison .......................... 107
  6.3.4 Pedestrian behavior modeling ....................... 108
  6.3.5 Experiment cases .................................. 108
  6.3.6 Observables ......................................... 109
6.4 Results and discussions .............................. 109
  6.4.1 Waiting time analysis of vehicles .................... 110
  6.4.2 Waiting time analysis of pedestrians ............... 113
  6.4.3 Throughput analysis ................................ 115
6.5 Conclusions ........................................ 115
7 MULTI-PARTY NEGOTIATIONS 117
  7.1 Introduction ........................................ 117
  7.2 Theory .............................................. 118
    7.2.1 V2V negotiation .................................. 120
    7.2.2 Negotiation workflow .............................. 120
  7.3 Implementation ...................................... 123
7.4 Results and Discussion .............................. 124
  7.4.1 Average waiting time .............................. 124
  7.4.2 Frequency distribution of waiting times ......... 126
  7.4.3 Throughput analysis ................................ 127
7.5 Conclusions ........................................ 127
8 DISCUSSION 129
  8.1 Cost-benefit analysis ................................. 129
  8.2 Major discussions and limitations ...................... 130
    8.2.1 Cultural variations in language of traffic .... 130
    8.2.2 Simulation constraints ............................ 130
    8.2.3 Pedestrian behavioral risks ....................... 131
    8.2.4 Ensuring an agreement ............................. 132
  8.3 Evaluation of overall hypothesis ....................... 133
9 CONCLUDING REMARKS AND FUTURE DIRECTIONS 137
  9.1 Contributions of this thesis .......................... 137
  9.2 Future directions .................................... 139

BIBLIOGRAPHY 143
## LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1</td>
<td>Vehicle-pedestrian interaction scenario: The interaction environment is restricted to unregulated junctions where the pedestrian appears at the curbside and is attempting to cross the road (screenshot in SUMO).</td>
<td>57</td>
</tr>
<tr>
<td>Figure 2</td>
<td>The proposed vehicle-pedestrian negotiation framework.</td>
<td>58</td>
</tr>
<tr>
<td>Figure 3</td>
<td>Travel time series: Travel time of first 30 vehicles in the simulation for negotiation model (blue) and conservative model (red).</td>
<td>67</td>
</tr>
<tr>
<td>Figure 4</td>
<td>Time headway analysis with the pedestrian frequency of 35s.</td>
<td>69</td>
</tr>
<tr>
<td>Figure 5</td>
<td>Time headway analysis with the pedestrian frequency of 14s.</td>
<td>71</td>
</tr>
<tr>
<td>Figure 6</td>
<td>Exit time analysis: The exit timestamp of vehicles in SUMO is plotted against the simulation runtime. The above plot is shown for first 30 vehicles to visualize the pattern in traffic flow.</td>
<td>72</td>
</tr>
<tr>
<td>Figure 7</td>
<td>Throughput analysis: The graph shows the exit timestamp of each vehicle at intersection until the end of simulation (24000s). The two time series represent the negotiation (blue) and conservative (red) model.</td>
<td>74</td>
</tr>
<tr>
<td>Figure 8</td>
<td>Interaction at an unregulated junction where the vehicles moving in a flexible and variable queue are negotiating for the right of way with pedestrians waiting at the curbside to cross the road.</td>
<td>78</td>
</tr>
<tr>
<td>Figure 9</td>
<td>The proposed vehicle-pedestrian negotiation framework.</td>
<td>80</td>
</tr>
<tr>
<td>Figure 10</td>
<td>Example scenario: vehicle is finding gap between pedestrian groups.</td>
<td>84</td>
</tr>
<tr>
<td>Figure 11</td>
<td>Waiting time frequency distribution in negotiation model (NM) and conservative model (CM).</td>
<td>90</td>
</tr>
<tr>
<td>Figure 12</td>
<td>Waiting time patterns for vehicle and pedestrians in different experiment cases.</td>
<td>91</td>
</tr>
<tr>
<td>Figure 13</td>
<td>Accumulation (waiting queue size) analysis for vehicle and pedestrians in different experiment cases.</td>
<td>93</td>
</tr>
<tr>
<td>Figure 14</td>
<td>Interaction scenario with pedestrian’s risk computation.</td>
<td>99</td>
</tr>
</tbody>
</table>
Figure 15  The proposed vehicle-pedestrian negotiation framework. ........................................... 102
Figure 16  Interaction example with risk-averse pedestrians at time $t = 8s$ ................................. 104
Figure 17  Interaction example with risk-averse pedestrians at time $t = 12s$ ................................. 104
Figure 18  Interaction example with risk-averse pedestrians at time $t = 15s$ ................................. 105
Figure 19  Interaction example with risk-averse pedestrians at time $t = 17s$ ................................. 105
Figure 20  Interaction example with risk-taking pedestrians at time $t = 15s$ ................................. 105
Figure 21  Interaction example with risk-taking pedestrians at time $t = 25s$ ................................. 106
Figure 22  The interaction environment setup in SUMO. This is a zoomed view of the scene. The lane actually starts from a distance of 200m from the right. ................................................................. 107
Figure 23  Density graph for the waiting time data of vehicles recorded in different experiment cases in the negotiation model (a-c, e-g), and in the conservative model (d,h). .......................... 111
Figure 24  Cumulative distribution function (CDF) graph for waiting times of vehicles in different experiment cases. .......................................................... 112
Figure 25  Density graph for the waiting time data of pedestrians recorded in different experiment cases. .......................................................... 114
Figure 26  Cumulative distribution function (CDF) graph for waiting time of pedestrians in different experiment cases. .......................................................... 115
Figure 27  Multi-party traffic scenarios with non-conflicting movement of vehicles (in a right-hand traffic system). .......................................................... 119
Figure 28  Extending the previous negotiation model to multi-party negotiations seeking agreement with other conflicting parties to cross first. Here, $(i, j = 1 \ldots \pi; \pi > 1)$. ........................................... 120
Figure 29  Multiparty interaction scenario ................................. 123
Figure 30  The multi-party interaction environment implemented in SUMO. ................................. 123
Figure 31  Waiting times distribution for vehicles in Negotiation model (NM) and Conservative model (CM) for high pedestrian frequency. ........................................... 125
Figure 32  Waiting times distribution for pedestrians (high pedestrian frequency) ................................. 126
LIST OF TABLES

Table 1  Gesture classification for road intersection scenario ........................................................................... 49
Table 2  Gesture classification for worksite scenario ................................................................................................ 50
Table 3  Terminology .................................................................................................................................................. 61
Table 4  Time headway (TH) distribution for negotiation (NM) and conservative (CM) model (pedestrian frequency 35s). .................................................................................................................. 68
Table 5  Time headway (TH) distribution for negotiation (NM) and conservative (CM) model (pedestrian frequency 14s) ........................................................................................................................................ 70
Table 6  Vehicle-pedestrian flow combinations ......................................................................................................... 86
Table 7  Waiting time analysis of vehicles and pedestrians for negotiation model (NM) and conservative model (CM) ........................................................................................................................................... 88
Table 8  Vehicle queue size distribution for negotiation model (NM) and conservative model (CM) .................................................................................................................................................. 94
Table 9  Intersection throughput analysis for negotiation model (NM) and conservative model (CM) .................................................................................................................................................. 95
Table 10 Possible cases of risk to the pedestrians and corresponding action by the vehicle in that situation ................................................................................................................................................... 101
Table 11 The vehicles’ waiting times statistics (in sec) for different experiment cases ................................................. 110
Table 12 Waiting time frequency distribution of vehicles for different experiment cases when pedestrian frequency is high ........................................................................................................................................... 112
Table 13 Waiting time distribution of vehicles for different experiment cases when pedestrian frequency is low ................................................................................................................................................ 113
Table 14 The pedestrians’ waiting times statistics (in sec) for different experiment cases ........................................ 113
Table 15 Intersection throughput (vehicles/hour) for different experiment cases ............................................................. 115
Table 16 Possible cases of risk to the pedestrians and corresponding action by the vehicle in that situation ................................................................................................................................................... 115
Table 17 Average waiting times of vehicles in different experiment cases .................................................................................. 122
Table 18 Frequency distribution of waiting times of vehicles in different experiment cases ........................................ 125
Table 19 Summary of performance for different models. WT denotes average waiting time ................................................................................................................................................ 134
ACRONYMS

V2V   Vehicle-to-Vehicle
V2I   Vehicle-to-Infrastructure
V2P   Vehicle-to-Pedestrian
V2X   Vehicle-to-anything
GPS   Global Positioning System
Wi-Fi Wireless Fidelity
NTSB  National Transportation Safety Board
SAE   Society of Automotive Engineers
NHTSA National Highway Traffic Safety Administration
SUMO  Simulation of Urban MObility
TraCI Traffic Control Interface
WHO   World Health Organisation
LED   Light Emitting Diode
LCD   Light Crystal Display
AutonoMI Autonomous Mobility Interface
AEVITA Autonomous Electric Vehicle Interaction Testing Array
CES   Consumer Electronics Conference
DSRC  Dedicated Short Range Communications
TTC   Time to Collision
CNN   Convolution Neural Networks
RNN   Recurrent Neural Network
ADAS  Advanced Driver Assistance Systems
POMDP Partially Observable Markov Decision Processes
SVM   State Vector Machines
FCFS  First-Come-First-Serve
UK    United Kingdom
USA  United States of America
MUTCD  Manual on Uniform Traffic Control Devices
TH  Time Headway
NM  Negotiation Model
CM  Conservative Model
RT  Risk Taker
RA  Risk-Averse
SR  Social Rules
PC  Physical Constraints
PHF  Pedestrian High Frequency
PLF  Pedestrian Low Frequency
PMF  Pedestrian Medium Frequency
HF  High Frequency
LF  Low Frequency
VNT  Vehicle Normal Traffic
VHT  Vehicle Heavy Traffic
CDF  Cumulative Distribution Function
SG  Straight Going vehicles
LT  Left Turning vehicles
s  Seconds (time)
m  meters (length/distance)
Self-driving vehicles are expected to operate on roads in coming years which are progressing through different levels of technology advancements. The Society of Automotive Engineers (SAE) International provided a taxonomy for six levels of driving automation, ranging from no driving automation to full driving automation (SAE, 2016), which was later adopted by the U.S. Department of Transportation’s National Highway Traffic Safety Administration (NHTSA, 2016). The Level 0 of vehicle automation is no-automation and the driver has complete control of the vehicle, while Level 1 is function-specific automation where the vehicle can automatically assist with some control functions. Level 2 is a combined function automation in which at least two functions are automated, like cruise control and lane catering. Level 3 is limited self-driving automation where the vehicle performs all safety-critical functions and monitors roadway conditions, and the driver can have occasional control with sufficiently comfortable transition time. Level 4 is high automation in which the vehicle performs all driving functions autonomously under certain conditions\(^1\), however, the driver can still control the vehicle when required. Current self-driving vehicle technologies, like the ones of Google and Tesla, can be classified somewhere between Level 3 and Level 4 automation. The highest Level 5 is full automation which means the self-driving vehicle will operate without any intervention from the driver in all conditions, which poses also a major challenge for them: their interaction with the other human road users.

The road traffic is fundamentally governed by road rules and regulations, but in many situations, the road users may not necessarily act according to the laws, for example in many cases the driving speed patterns of drivers deviate from the actual road speed limits (Wilde, 1980). The road traffic can sometimes be self-organizing, or even be chaotic, where explicit rules cannot always be determined (Färber, 2016). Even the regulated traffic codes do not guarantee conflict resolution in every situation, especially when it comes to driver-pedestrian conflicts for the right of way. In such situations, implicit rules among road users facilitate their safe movement on roads.

The pedestrians always having the right of way is not clear. Traffic guidelines for many countries, including UK, Australia, US, state the right of way\(^2\) to pedestrians at the intersection while the vehicle is

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\(^1\) The SAE levels of driving automation are defined by reference to specific dynamic driving tasks (DDT) which is listed in the SAE J 3016-2018 document (SAE, 2016)

\(^2\) right of way varies from state to state in the US while only NSW state in Australia explicitly states right of way to pedestrians even at unmarked crosswalks
turning, at zebra crossings, and children’s crossings, and at marked foot crossings at signalized junctions (when pedestrian lights are on). However, in other situations, the law gives right of way to no one but states who must yield in order to maintain safety on roads (Shinkle, 2016). Even the general traffic safety guidelines suggest drivers to look out for pedestrians at pedestrian crossings, intersections, around parked vehicles, near schools, and shopping centers. Moreover, right of way conflict is not limited to unmarked crosswalks but also at local roads in suburban settings, residential streets, busy CBD roads, and small suburban shopping lanes.

Similarly, pedestrians are suggested to prefer crossings instead of running through the middle of the driveways. In many such situations, Section 1 of the German Highway Code always applies: “Participating in road traffic requires constant caution and mutual consideration” (p. 1). It follows that evaluating and communicating each other’s intentions to assess other participants’ behavior is necessary in order to maintain the safety of road users. In addition to formal rules, there also exists an informal language of traffic that help road users resolve their crossing conflicts.

Imagine a pedestrian approaching an intersection to cross, and at the same time, a vehicle (with a driver) arrives there from a conflicting direction. If it is not a regulated intersection, there is a right of way conflict, and Who is going to pass first is generally a matter of negotiation between a driver and a pedestrian. The driver, when they discover this pedestrian, may either slow down the vehicle and wave at the pedestrian to allow them to cross first; or in other case, the driver may continue moving with their current speed to indicate their intention to pass first. Similarly, the pedestrian might show a gesture to encourage drivers to go first, or in other situations the drivers can sense pedestrians’ crossing intentions through their body movements in which case they prepare to yield to the pedestrian. Such an informal mode of communication helps both drivers and pedestrians to quickly anticipate what is going to happen next.

The question is: How will self-driving vehicles fit into this complex social system? One of the challenges for these vehicles is their interaction with human road users, including pedestrians, cyclists, and other human drivers. In current traffic, it is observed that pedestrians communicate their intentions to drivers via gestures and gaze (Sucha, 2014). Similarly, drivers use head or hand signals or electrical signals fitted to the vehicle to communicate with pedestrians. But with self-driving

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5 Available at http://germanlawarchive.iuscomp.org/?p=1290 (accessed online on Feb 10, 2018)
vehicles, there is no human behind the steering wheel, and hence one of the most prevalent communication channels is lost – the driver. The industry is working on alternative communication concepts between self-driving vehicles and pedestrians such as projecting crosswalk for the pedestrians (BMW, Mercedes), text message displays (Google), or light belts (Nissan). However, these channels only communicate the vehicles’ intentions and do not engage in a negotiation. They may fail to resolve the potential conflicts at, for example, unregulated intersections where vehicles have to compete for a right of way with pedestrians, or else, always stop for them. Currently self-driving vehicles, autonomous in their decision making, rather conservatively stop for pedestrians intending to cross the road. This behavior is slowing them down considerably (Millard-Ball, 2018). Therefore, more effective interactive negotiation techniques among self-driving vehicles (in short, vehicles) and pedestrians are required.

1.1 BACKGROUND AND MOTIVATION

Most road fatalities in the urban environment concern pedestrians. The main cause is human driver error (WHO, 2015). Future self-driving vehicles are expected to reduce these errors and increase the safety on roads (Winkle, 2016). However, the theoretical predictions of these vehicles’ impact on traffic, in contrast, are more varied. These predictions fall into two types of impacts on the pedestrian – one emphasizing on the safe behavior of vehicles towards pedestrians, while others raising issues of their erratic behavior towards pedestrians. So far mostly theoretical reviews on the vehicle-pedestrian interactions are focused and there is far less research regarding these interactions in real-life settings.

The vehicles are programmed to obey the rules of the road and to wait for pedestrians to cross, even at unmarked crosswalks (Millard-Ball, 2018). When it comes to their interaction with pedestrians, related industrial research is mainly focused on defensive measures. A passive measure of this sort is the airbag protection for pedestrians (Switkes, Khaykin, and Larner, 2015) to ensure their safety. Another passive measure is a general concession to yield, expressed in research into interaction with pedestrians exploring potential communication channels for the vehicle to tell a pedestrian it sees them and is expecting them to cross in front (Keferböck and Rieners, 2015). Such passive interaction measures clearly make the vehicles safer for pedestrians at the cost of the vehicle’s speed. However, such safe behavior has also undesirable consequences. A game theoretic analysis by Millard-Ball (2018) on vehicle-pedestrian interactions in future suggests that safer (or conservative) future self-driving vehicles would provoke the pedestrians to step out to cross since they trust that the vehicle will yield to them. For example, in the future it will be easy
for playful children on roads to interfere with the vehicle’s operations – as a consequence, the vehicle will keep standing. Theoretically, because of the widespread adoption of such vehicles, the future urban traffic is expected to slow down significantly.

Other researchers, on the contrary, highlight the safety concerns in mixed traffic scenarios, i.e., self-driving vehicles sharing the road with human road users expected in the future on roads (Sivak and Schoettle, 2015). Replacing human drivers with autonomous systems may result in ambiguities in understanding other road users’ behavior, which is evident from the recent crashes of vehicle prototypes (Richtel and Dougherty, 2015a).

Social interaction among road users is necessary to guarantee everyone’s safety on roads, but also to ensure proper traffic flow (Rasouli, Kotseruba, and Tsotsos, 2018). There is still a social interaction void in the behavior of these vehicles. In everyday situations, human drivers tend to establish eye contact with the pedestrians expressing their intention to pass first, while they can also judge pedestrians’ intentions through their body gestures or signals such as raising a hand to stop or waving to let others pass (Langton, Watt, and Bruce, 2000). Vice versa, even pedestrians assess their risk of taking action and risk-taking attitudes differ among individual pedestrians (Li, 2013, 2014; Lobjois and Cavallo, 2007). Individual levels of risk-taking make pedestrian behavior harder to predict. In informal communication, the vehicle (or currently, the driver) can anticipate the pedestrian’s risk and make an intuitive guess of their intended actions (Himanen and Kulmala, 1988), for example, from their gestures or gaze. Now the vehicle, if they are sure that the pedestrian’s intention is to yield, can take the opportunity to pass first. In any situation, either the driver or pedestrian yield to the other to maintain safety on roads. Though invisible, this negotiation happens every day among drivers and pedestrians, especially at unmarked intersections. However, for a self-driving vehicle, mimicking such behavior has few challenges, one of them being the non-universality of signaling gestures. Also, these social cues may be ignored by some pedestrians and drivers (civil inattention) leading to indiscipline on roads (Goffman, 1963; Kadali and Vedagiri, 2013; Özkan et al., 2006; Patterson et al., 2007). Such issues exacerbate the challenges for future vehicles.

Few researchers argue that the future self-driving vehicles are required to exhibit a socially acceptable behavior that is understood by human road users, especially pedestrians (Müller, Risto, and Emmenegger, 2016; Shladover, 2016). One such aspect of this social behavior is traffic negotiation with pedestrians, which is addressed in this thesis. This work attempts to consolidate the observed elements of social behavior in traffic into a negotiation model for vehicles and pedestrians. From the above discussion, assuming that as long as these social rules are lacking, the design of these vehicles’ behavior
will be conservative; this work aims to improve traffic throughput by active social engagement.

1.2 CHALLENGES FOR A SELF-DRIVING VEHICLE

Negotiation in traffic poses many challenges for a self-driving vehicle. This section gives a summary of a few challenges which also concerns the work presented in this thesis.

1.2.1 Interpreting language of traffic

Pedestrians in their intention to cross the road engage with drivers in some interaction. As discussed above, this interaction is through the exchange of cues such as gaining attention through eye gaze or using gestures to indicate one’s desire (Langton, Watt, and Bruce, 2000). They do so at unmarked locations but often even at marked pedestrian crossings or signaled intersections to negotiate for the right of way (Sucha, 2014). Human drivers are able to judge the pedestrian’s intention through such cues and react to the situation (Schmidt and Färber, 2009). Similarly, pedestrians can also intuitively estimate the intentions of drivers from the driving behavior cues, or hand waving. But for self-driving vehicles, it is still challenging to understand this informal language of traffic (Färber, 2016). Furthermore, cultural differences in such informal language of road users makes the decision-making for robotic vehicles more difficult (Özkan et al., 2006; Patterson et al., 2007).

1.2.2 Intent perception and communication

Behavioral psychology of pedestrians is complex which influences their crossing decisions on road (Harrell, 1991; Ishaque and Noland, 2008; Rasouli, Kotseruba, and Tsotsos, 2017). Existing studies show that factors such as pedestrian demographics, social factors, dynamic factors, and traffic conditions have a major impact on pedestrians’ crossing intentions (Rasouli and Tsotsos, 2019). However, pedestrians might behave differently when confronted with self-driving vehicles compared to conventional vehicles. Understanding of pedestrians’ intentions on the road are crucial to autonomous driving to infer their possible actions. The challenge for future vehicles is to incorporate various contextual information in their pedestrian intention estimation algorithms (Brouwer, Kloeden, and Stiller, 2016; Madrigal, Hayet, and Lerasle, 2014). Vice-versa, the vehicle’s intent should be clear to the pedestrians so another challenge is to build an effective mode of communication to communicate vehicle’s intent to human road users (Mahadevan, Somanath, and Sharlin, 2018).
1.2.3 Social behavior

While the signalized junctions are controlled by traffic laws, informal social rules play an important role at unmarked intersections (Dey and Terken, 2017; Färber, 2016). For example, pedestrians generally allow heavy vehicles or a queue of vehicles to pass first in an effort to maintain a smooth traffic flow (Himanen and Kulmala, 1988). Vice versa drivers accept to stop for a waiting pedestrian group (Helmers and Aberg, 1978). The road users understand the intentions of other users, simulate the consequences of a particular planned action, and then react accordingly. Self-driving vehicles do not exhibit such social behavior yet, and also lack the ability to take human-like decisions in situations where there might be a conflict among road users for the right of way (Keferböck and Riener, 2015; Vinkhuyzen and Cefkin, 2016). A lack of social understanding might result in safety issues among road users (Müller, Risto, and Emmenegger, 2016). As such, apart from the regular laws, it is also necessary to incorporate informal social rules in their decision-making methods.

1.2.4 Agreement in negotiation

An important aspect of social behavior in traffic is reaching an agreement with the other road users to get the right of way. Human drivers do it by intuitive assessment of risks given the perceived cues and estimated intentions. However, this type of assessment becomes challenging for self-driving vehicles due to the uncertainty in recognizing the intentions of the pedestrians. Additionally, individual personalities also have an effect on the level of agreement in their behaviors. For example, children are more likely to ignore the risks involved and show a sudden change in their crossing behavior (Demetre et al., 1992). Even among adult pedestrians, the different personalities of pedestrians influence their risk-taking attitudes (Oxley et al., 1997; Schmidt and Färber, 2009). The risk-taking behaviors of pedestrians reflect their tendency to yield or not, which in turn, affects the certainty of agreement in a negotiation. Dealing with various risk-taking behaviors of pedestrians in traffic is another challenge for future vehicles.

The challenges that self-driving vehicles will face while encountering human road users are more complex than only inferring a human presence around them. Though the work in this thesis only focuses on self-driving vehicles’ negotiations with pedestrians and does not provide a solution to all the associated problems with self-driving vehicles, yet the above challenges are related to the negotiation problem. As such, a comprehensive review of challenges for self-driving vehicles and various possible multi-disciplinary approaches addressing these issues are discussed in Chapter 2.
1.3 Research objectives and hypothesis

The downside of conservative behavior of self-driving vehicles is that it will slow down the urban traffic in the future. Given the former premise, the overall objective of this research is to propose a framework for negotiations between self-driving vehicles and pedestrians for the right of way. The overall hypothesis of this research is that a vehicle’s chances for the right of way increase with negotiations, which will consequently reduce their average waiting time and improve the overall throughput at intersections when compared to the vehicle’s conservative behavior. In this thesis, the negotiation problem has been investigated in five stages; the research objectives at each stage are addressed in five different chapters, as described below:

1. Universality of gestures in traffic (Chapter 3): In order to ground research on some conventionalized human behavior, the preliminary work in this thesis focused on the study of traffic control officers’ gestures directing the general traffic at road intersections and worksites. This research aims to catalogue the conventions related to particular tasks and find universal commonalities as well as differences between cultures and regulatory frameworks. The hypothesis of this research is that a universally accepted set of gestures can be identified from the rules used by traffic controllers to direct road traffic. To test this hypothesis, the following research questions are investigated:

   a) Can the hand signals used by traffic control officers for standard situations such as directing the traffic at 4-way junctions, directing the traffic at emergency spots or road maintenance work areas, or guarding pedestrians at pedestrian crossings, be catalogued and categorized?

   b) What are the commonalities and differences between the conventions in different regulatory frameworks?

   c) Is there a universally accepted set of gestures for certain intentions?

   d) Do traffic control officers use other elements of expressions (like eye gaze, instruction batons) along with hand signals to direct vehicles on the road? What are these situations?

2. Vehicle–Pedestrian negotiation framework (Chapter 4): The objective is to conceptualize the negotiation process between a pedestrian and a self-driving vehicle which addresses the following research question:

   a) What are the steps in self-driving vehicle-pedestrian negotiations?
b) Can self-driving vehicle successfully negotiate with pedestrians for their right of way at intersections with an understanding of pedestrian’s intentions and physical constraints, in order to reduce their waiting times?

The hypothesis of this research is that the negotiation between self-driving vehicles and pedestrians will result in better coordination among both parties, reduce the travel time of vehicles, and thus improve the overall traffic flow at intersections compared to conservative vehicles.

3. Social rules in negotiation (Chapter 5): This chapter extends the above model and introduces negotiation strategies between multiple vehicles and multiple pedestrians, interacting in groups. The following research questions are investigated in this chapter:

   a) Which informal social rules exist among human drivers and pedestrians affecting their crossing decisions?

   b) In addition to physical constraints, can social rules increase the chances for self-driving vehicles’ successful negotiations with pedestrians for their right of way?

The hypothesis of this research is that negotiation by social rules can significantly lower waiting times for vehicles and thus improve the overall intersection throughput, compared to their conservative counterpart.

4. Risk-based negotiation (Chapter 6): The previous model is further improved by allowing individual decision-making, considering different risk-taking attitudes of pedestrians, and defining possible strategies for the vehicles to negotiate with them for the right of way. Chapter 6 introduces a pedestrian’s risk-based model for negotiation between multiple vehicles and multiple pedestrians, in which the following research question is addressed:

   a) Does pedestrian’s risk-averse attitude along with the influence of social rules, increase the chances of successful negotiations for self-driving vehicles?

The hypothesis of this research is that negotiations will reduce the waiting times for vehicles and improve the overall intersection throughput, compared to conservative vehicles.

5. Multi-party negotiation (Chapter 7): The last objective of this research to demonstrate the applicability of the social rules to a more complex environment, i.e., also adding vehicles from other directions, and other pedestrian groups. The following research question will be investigated:
a) Will social rules also improve the flow of multi-directional incoming traffic at intersections, while reducing the risk of collisions?

The hypothesis of this research is that compared to the vehicle’s conservative behavior, social rules of negotiations between connected vehicles and pedestrians approaching the intersections from different directions will improve the intersection throughput and their waiting times.

All of the above research questions correspond to the overall research theme – negotiations for the right of way. From the perspective of negotiations, self-driving vehicles need to understand the intentions of pedestrians exhibiting the language of gestural interaction. As such the preliminary work on the universality of gestures was necessary to understand whether there exists a common language of interaction in traffic. The rest of this thesis focus on developing and testing the vehicle-pedestrian negotiation framework. In summary, the negotiation process between a single vehicle and a single pedestrian is studied first based on physical constraints. A further objective was to extend this model by introducing scenarios of negotiation between multiple vehicles and multiple pedestrians. Decisions are no longer made on physical constraints alone but have now to consider some social rules as well. In addition to social rules, the vehicles will also consider different risk-taking behaviors of pedestrians. Then finally the scalability of the proposed model is demonstrated in multi-party traffic scenarios.

1.4 Thesis Contributions and Outcomes

This thesis presents a novel model for negotiation, allowing self-driving vehicles to negotiate with pedestrians for their right of way. The model allows for multiple vehicles and multiple pedestrians, individual decision making, and different personalities, following some social rules. The model is designed to not compromise safety – when the vehicle is not certain about agreeing with a pedestrian then it always yields to them. A summary of the contributions in this thesis is here:

- laying the foundation for the understanding of gestures by self-driving vehicles, by classifying different hand signal rules used by traffic controllers and identifying the general language to direct traffic at controlled road sites.

- proposing the first negotiation model between self-driving vehicles and pedestrians to overcome the downsides of slower conservative self-driving vehicles.

6 More details in Chapter 4
• the introduction of informal and fuzzy social rules for decision making in traffic enabling self-driving vehicles to take human-like decisions to resolve conflict situations.

• the consideration of different risk-taking attitudes of pedestrians in order to improve vehicle throughput without compromising safety.

• scaling the social rules to improve the flow of multi-directional incoming traffic at intersections

The proposed negotiation model is implemented using the SUMO\textsuperscript{7} traffic simulator and MATLAB\textsuperscript{8} toolbox. In the experiments with this model, the waiting times of vehicles and the intersection throughput are analyzed for different distributions of vehicle and pedestrian flow. These parameters are then compared to the conservative behavior model in which vehicles are slowing down when sensing pedestrians intending to cross the road. Also, qualitative cost-benefit analysis for both self-driving vehicles and pedestrians is discussed in terms of the social, economic, and environmental impact of these negotiations.

To our knowledge, a negotiation model introducing social rules for decision making in traffic is novel. This work demonstrates how negotiation reduces the conflict of interests between vehicles and pedestrians in different traffic conditions and balances the right of way among them. The simulation results show that the negotiations reduce the waiting times of vehicles and improve the overall intersection throughput compared to the conservative vehicle behavior. The reduction of waiting times for the vehicles is coming at the cost of pedestrians, but the simulation shows also that these waiting times for pedestrians do not exceed those at signalized intersections.

1.5 THESIS STRUCTURE

The current chapter presents the motivation for this thesis, and the research objectives and hypothesis addressed in this work. The rest of the thesis is organized as follows: Chapter 2 conducts a systematic review of literature across multiple disciplines, exploring existing studies on conventional vehicle-pedestrian interactions, and the recent theoretical and empirical studies on socially-intelligent self-driving vehicles. This chapter establishes the foundations for the proposed negotiation framework.

The next five chapters discuss the proposed models and experiments corresponding to each research question and hypothesis listed in Section 1.3. Chapter 3 investigates the universality of gestures in

\textsuperscript{7} http://sumo.dlr.de
\textsuperscript{8} http://mathworks.com
traffic. Chapter 4 introduces the conceptual vehicle-pedestrian negotiation framework. Chapter 5 conceptualizes the social rules of negotiations. Chapter 6 proposes a pedestrian’s risk-based negotiation model. Lastly, Chapter 7 demonstrates the scalability of the proposed model to multi-party traffic negotiations.

The final part of the thesis provides an overall discussion on the major findings of this work along with the limitations (Chapter 8). The overall conclusions and summary of the thesis is presented in Chapter 9 which concludes with prospective directions for future work.
In the context of socially-intelligent vehicles, this chapter constructs a link between related studies from different disciplines. Firstly, Section 2.1 reviews the current gaps in the social behavior of self-driving vehicles by providing evidence from existing studies in vehicle and pedestrian interactions. Afterwards, Section 2.2 studies the potential design solutions to embed social capabilities in self-driving vehicles, also providing a review on the communication challenges for vehicles. Next, a comprehensive review of pedestrian crossing behavior is done in Section 2.3 including present studies involving self-driving vehicles. Following this discussion, Section 2.4 focuses on practical systems to predict pedestrians behaviors in traffic. Lastly, Section 2.5 studies various conflict-resolution methods in traffic. Based on this review the contributions of this thesis are highlighted.

2.1 Socially Acceptable Vehicles

The driverless vehicle industry including Google, Tesla, Nissan, and others are already testing their vehicle prototypes. The integration of multiple sensors on-board these vehicles have improved their ability to sense their surroundings. With improved sensor capabilities, vehicle’s decision-making in traffic is also expected to improve (Schwarting, Alonso-Mora, and Rus, 2018). While this may be true, apparently it is still hard to predict if sensor capabilities can ever come close to human-like capabilities to make instant decisions in complex considerations in traffic (Casner, Hutchins, and Norman, 2016; Martens and Beukel, 2013; Müller, Risto, and Emmenegger, 2016). Moreover, earlier test runs suggested that driverless vehicle prototypes failed to adapt to the human behavior (Richtel and Dougherty, 2015b). As such, some experts even argue that within the coming decade the fully automated driving is feasible only for restricted and specific environments, and it will take a few decades for self-driving vehicles to run autonomously on roads in all conditions. (Shladover, 2016).

2.1.1 Social behavior of self-driving vehicles

Self-driving vehicles will share the road with other road users, including pedestrians. These road users not only act out of a self-interest, and with regulations, but also sometimes react in response to social cues from other users. In order to integrate future vehicles into this social system, it is important that they appear intelligent to other road
users and exhibit a socially acceptable behavior (Vinkhuyzen and Cefkin, 2016). As such, Müller, Risto, and Emmenegger (2016) described them as social actors in traffic, and argued that the driverless vehicle is a part of a "complex socio-technical system which has to interact with all other actors in a socially acceptable manner" (p. 1).

Exhibiting a social behavior in traffic is one of the many challenges these vehicles will face before they are formally accepted as a part of the urban traffic. Social behavior here means the ability to understand other road users’ behavior (especially human road users), and to act accordingly. Understanding road users’ behavior involves the ability to distinguish between various types of road users and to interpret their actions. For instance, future vehicles should be able to distinguish between traffic control officers, pedestrians, and cyclists, and differences in their formal commands (hand signals, legal norms) and informal gestures (mostly of pedestrians) (Prakken, 2017). Apart from distinguishing various road users, another major challenge for self-driving vehicles is social interaction in a busy traffic intersection – places of heavy informal interaction among road users in order to resolve their conflicting intentions to cross a shared space. Especially in the context of interaction among drivers and pedestrians, social cues are exchanged among them, and negotiation happens for the right of way. Interaction can happen in any form, for example, drivers and pedestrians establish eye contact with each other in order to estimate each other’s crossing intentions (Rasouli, Kotseruba, and Tsotsos, 2018). Other social cues often used by pedestrians are their body gestures and hand signals, such as raising their arms to stop the vehicle, or waving to let them pass first (Langton, Watt, and Bruce, 2000). This informal communication becomes an indication to the drivers to yield to pedestrians. Additionally, a vehicle (or driver) slowing down is assumed to be yielding, while pedestrians tend to yield for high-speed, heavy-duty or a queue of vehicles (Himanen and Kulmala, 1988; Jensen, 2013; Lobjois and Cavallo, 2007). Such type of informal negotiations, involving the exchange of social cues, is necessary for maintaining safety on the roads and keeping the flow of traffic moving. However, the current design of vehicle lacks negotiation abilities. Social interaction involving self-driving vehicle is a relatively understudied field, as such, this thesis particularly focuses on describing self-driving vehicle-pedestrian negotiations at unmarked intersections for the right of way.

2.1.2 Why is social interaction necessary?

In future, social interaction may play an important role in resolving traffic conflicts. Given that self-driving vehicles will be interacting with other users (for example, at road crossings), research implications in the area of human-robot interaction put further stress on the
importance of social interactions in future vehicle design. Social intelligence is necessary for many applications of robots where they are directly or indirectly involved in interactions with humans (Goodrich and Schultz, 2008). Researchers argue that robots should not just be programmed to avoid objects, especially when humans are involved (May, Dondrup, and Hanheide, 2015). Instead, humans should feel safe and comfortable when interacting with robots and both should have a mutual understanding of the situation. In the context of social robots (such as in assisted living (Broekens, Heerink, and Rosendal, 2009)), robots should actively engage in both verbal and non-verbal communications with humans, and human-robot mutual intentions should be clear (Breazeal et al., 2001; Shattuck and Woods, 1997; Watanabe et al., 2015).

Few empirical studies on human-robot interaction highlighted the impact of intent communication by robots in the perceived comfort of humans during the interaction. For example, May, Dondrup, and Hanheide (2015) conducted experiments using ‘robotic gaze’ and ‘direction’ indicators to communicate the robot’s navigation plan to the human participants. Their findings show that both forms (gaze and indicators) of communication improved human comfort during interactions. But communicating motion intent through direction indicators was the preferred mode among participants. The above study shows that the purpose of interaction also matters in the design of any form of communication. Similarly, other studies, using research robot prototype (Chadalavada et al., 2015) or virtual testing methods such as augmented reality (Bunz et al., 2016), show that projecting near future robot’s trajectory information on the floor by the robot is able to effectively improve the human response to the robot. The above studies in social robotics emphasizes the importance of intent communication (by machines) in human-machine interactions. This importance is further strengthened by conclusions of a survey-based study (Takayama, Dooley, and Ju, 2011), which suggested that a communicative robot is likely to be perceived as appealing, approachable, and sure of its subsequent actions, compared to non-interactive robots. Furthermore, a robot exhibiting social behavior appears more reliable and predictable to humans (Turnwald et al., 2016), which in turn, guarantees safety of all, including humans involved in the interaction (Dautenhahn, 2007; Hoff and Bashir, 2015; Hoffman and Ju, 2014; Lee and See, 2004). Similar to social robots, future self-driving vehicles are also required to communicate their intent to human road users in order to maintain safety on roads and gain public acceptability. However, translating the communicative properties of social robots to self-driving vehicles is not straightforward. Similar type of interaction is
challenging for vehicles largely due to constraints on interaction distance and sensor capabilities; for example, in one of the study it has been shown that speech recognition, and face/hand gesture recognition by robots performs adequately up to distances of 2.5m from the human subject (Mead and Matarić, 2015). This means current technology does not support gestural communication between self-driving vehicles and pedestrians in which case interaction distances may be more than 50m.

2.1.3 Theoretical reviews on safe vehicle design

In the context of social behavior capabilities of self-driving vehicles, let us first highlight the reviews on the current state of self-driving vehicle designs. An important motivation behind replacing human-driven vehicles with self-driving vehicles is reducing the number of accidents caused due to human driver errors (WHO, 2015). In a crash report by the US motor vehicle department, around 4743 pedestrian accidents and 726 cyclists fatalities were recorded in the United States in the year 2012, which represents 14% of the total road incidents (NHTSA, 2013). Around 70% of the fatalities reported were due to human driver error.

Methods to ensure pedestrian safety have been particularly explored. For example, pedestrian collision avoidance mechanisms are programmed in the vehicles to keep them away from pedestrians at critical times (Llorca et al., 2011). Furthermore, to prepare the vehicle for worst case scenarios they are deployed with pedestrian protection systems to detect when a collision is unavoidable, and activate emergency brakes and pedestrian airbags\(^2\) to minimize the expected casualties (Llorca et al., 2009). In context of self-driving vehicles, safety will be a primary concern, and in order to maintain safety on the road, it is expected that they will be programmed to drive carefully.

In other studies also it is pointed out that self-driving vehicles are expected to be safer than human-driven vehicles (Winkle, 2016). This is because self-driving vehicle will follow the rules of the road, including the rule to yield to pedestrians whenever vehicle encounters any pedestrian around them (Millard-Ball, 2018; Ohn-Bar and Trivedi, 2016). Theoretical reviews on this safe vehicle design suggest that assertive pedestrians, in future, will have an adverse effect on the flow of vehicles (Millard-Ball, 2018). The former argument also suggests the following situations in future: In urban areas with a high density of pedestrians, self-driving vehicles might come to a standby if they are conservative; a similar situation can be imagined when playful children may not allow the vehicle to move by standing in front of them.

\(^2\) The pedestrian airbag concept was designed to protect pedestrians in the case of a frontal impact with the car
Notwithstanding their safe design, few researchers also highlighted the safety concerns in mixed traffic scenarios where self-driving vehicles will be sharing the road with human road users (Sivak and Schoettle, 2015). Replacing human drivers with autonomous systems may result in ambiguities in self-driving vehicle’s understanding of other road users’ behavior, which is evident from the recent crashes of these vehicle prototypes (Richtel and Dougherty, 2015a). The vehicle might show erratic behavior towards pedestrians, or even run into a social dilemma of running over pedestrians or sacrificing their passenger to save the pedestrians (Bonnefon, Shariff, and Rahwan, 2016). However, the question of unavoidable crashes in a social dilemma is out of the scope of this thesis’s discussion.

Nevertheless, it is clear that if conservative vehicles are confronted with any pedestrians, vehicles will prepare to slow down for the pedestrians. Consequently, urban traffic will be slowed down. The objective of this thesis is premised on the adverse impacts of conservative behavior of self-driving vehicles on traffic. To avoid a highly conservative behavior that may slow down the traffic, future self-driven vehicles will have to negotiate with human road users, for example, with pedestrians to resolve crossing conflicts – the impact (of which) is discussed later in Chapter 8. The next two sections focus on exploring the nature of interactions in traffic in the presence of conventional (human-driven) and self-driving vehicles.

2.1.4 Studies on driver-pedestrian interactions

It is expected that various road users have a similar interpretation of their surroundings including other users’ intent, otherwise collisions are likely to happen (Endsley, 1995). The following review particularly focuses on driver-pedestrian interactions. Pedestrians’ interactions with conventional vehicles (or say drivers) have been studied in the literature. These interactions may develop as a consequence of safety concerns among road users (Lundgren et al., 2017; Sucha, Dostal, and Risser, 2017); and the way they are developed are affected by individual expectations from others on the road (Zhou, Horrey, and Yu, 2009). Furthermore, the drivers’ interactions with pedestrians become complex because of their different motivations and cognitive states (Mwakalonge, Siuhi, and White, 2015). These interactions are further affected by various factors such as behavior of other road users (Rosenbloom, 2009; Zhou, Horrey, and Yu, 2009), pedestrians’ crossing speeds (Knoblauch, Pietrucha, and Nitzburg, 1996), vehicle speeds and stopping distance (Schneemann and Gohl, 2016; Sun et al., 2015; Varhélyi, 1998), traffic density (Wang et al., 2010), road infrastructure and weather conditions (Knoblauch, Pietrucha, and Nitzburg, 1996; Sun et al., 2015), and also the demographics of
road users (Lobjois and Cavallo, 2007; Oxley et al., 1997; Tom and Granié, 2011).

Some traffic situations might be ambiguous where it is not clear who has the right of way, and that is where negotiation is needed. In such situations, communication between drivers and pedestrians happens with the exchange of non-verbal cues (such as hand signals, gaze interaction, etc.). Several empirical studies on vehicle-pedestrian interactions demonstrate the effect of non-verbal communication on the nature of interactions, as discussed next. One of the important cues in driver-pedestrian interactions is eye gaze. The study by Luoma and Feltola (2013) shows that pedestrians, in general, face the traffic while crossing to ensure their safe movement. Another related study by Rasouli, Kotseruba, and Tsotsos (2017) on driver-pedestrian interactions concluded that 90% of the times pedestrians are found looking at the oncoming traffic before taking a decision to cross. They also argue that cues like looking and glancing are the most used forms to communicate intent to the vehicle (with a driver) in traffic. A field study by Sucha, Dostal, and Risser (2017) also found that pedestrians’ crossing decisions are affected by cues from drivers such as gestures and 84% pedestrians were observed to seek the attention of a driver through an eye contact. However, only 34% of the drivers acknowledged by seeking an eye contact which suggested a major difference in their respective needs for mutual communication. This analysis, however, is limited by the observations of the observers about evident “eye contact” between drivers and pedestrians during the study, as the operationalization of eye contact was not done in the experiments. The above review suggests that facing the approaching traffic, involving gaze and body movements, is a more general form of seeking attention among pedestrians.

Likewise, the driver’s behavior is also influenced by non-verbal communications. Field experiments by Guéguen, Meineri, and Eyssartier (2015) show that when when pedestrians attempted gaze interactions with drivers, it increased the number of drivers who stopped at crossings by more than 20%. Other positive influences on driver behaviors are also demonstrated in the form of reduced cases of sudden breaking and increase in their slowing down behaviors (Ren, Jiang, and Wang, 2016). An exchange of gaze between drivers and other road users not only confirms that road users are noticed, but it also increases their compliance with road instructions (Hamlet, Axelrod, and Kuerschner, 1984). Similar other empirical studies show that non-verbal communications increase the driver’s tendency to cooperate during negotiations and in turn yielding more easily at crossings (Crowley-Koch, Van Houten, and Lim, 2011; Guéguen, Eyssartier, and Meineri, 2016; Nasar, 2003; Zhuang and Wu, 2014).

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3 Operationalization is a process of defining the measurement of a phenomenon that is not directly measurable
The above review suggests that informal negotiations happen everyday on roads. Based on the above evidences, Chapter 4 proposes a negotiation model between a vehicle and a pedestrian. The different forms of interactions discussed above are a starting point for vehicle-pedestrian negotiations which will be discussed in Chapter 4.

2.1.5 Analysing interactions with self-driving vehicles

Unlike pedestrians’ interactions with conventional vehicles, the nature of interactions with self-driving vehicles is relatively understudied. Till now, studies in the context of autonomous driving mainly focused on analyzing pedestrian’s perceived risk of crossing when interacting with them. It is expected that communication needs and the nature of interaction will change when fully automated vehicles are introduced in the traffic system (Habibovic et al., 2016). However, the arguments on this issue are divided among researchers.

Millard-Ball (2018) relates the interaction between a self-driving vehicle and a pedestrian to the game of crosswalk chicken in which a player’s optimal choice depends on the possible action of their opponent. He argues that when confronted with autonomous vehicles, pedestrians will always choose to cross first. Pedestrians, knowing that the vehicle will always yield to them, will be assertive and their perceived risk, in this case, will not even exist. As such there will be no need for any form of communication between them, he further adds. Interestingly, in one of the field studies by Rothenbücher et al. (2016) similar conclusions were drawn. The implication of their study is that pedestrians’ behaviors at crosswalks do not change while encountering a (self-driving) vehicle with a ghost driver\(^4\), compared to encounters with drivers; eventually, the pedestrians cross the street without any hesitation. This study, however, is subject to bias in the environment and participants selection. The study was conducted on a university campus where participants had a better understanding of the expectations from the experiment. Also, driving is usually safe in the campus environment which affected the risk acceptance behavior of the participants. As such it can be said that results from this study do not align with the real-life settings.

On the contrary, other studies suggest that the introduction of self-driving vehicles in traffic may lead to a notable change in the perception of pedestrians about self-driving vehicles compared to conventional vehicles (Habibovic et al., 2016; Lundgren et al., 2017). Few research groups conducted experiments on evaluating pedestrians’ crossing comfort against different autonomous driving behavior of vehicles. In these experiments, different behaviors of ‘drivers’ were

\(^4\) In this study, participants encountered a vehicle that appeared to have no driver, but which in fact was driven by a human confederate hidden inside, termed as a ghost driver.
disguised as autonomous driving behaviors, so pedestrians’ interactions were typically linked to the changing role of the driver who becomes a more passive participant in the interaction. One such study by Lagstrom and Lundgren (2015) considered several scenarios of driver distraction at crossings during experiments. Pedestrians’ crossing intent was observed against the drivers’ attention (eye contact), and different driver distraction scenarios (staring on the road, reading the newspaper, and talking over the phone). Their results show a positive interaction when the driver made an eye contact with pedestrians. However, in other cases the drivers’ distraction led to an increased perceived risk of crossing among pedestrians, and the majority of them did not cross. In a similar study by Habibovic (2018), the pedestrians stated in post-questionnaires that “they would look for confirmation from the ‘driver’, and that future vehicle should clearly inform them about their mode and intent”. Their study implied that pedestrians’ acceptability for future vehicles will increase if the intent is clear to them. A proper communication channel would eliminate possible ambiguities which may arise without the driver’s presence. The above conclusions, however, are also supported by other experiments in real-traffic settings where interactions between self-driving vehicles and pedestrians have been investigated (Böckle et al., 2017; Merat, Madigan, and Nordhoff, 2016). Yet, there are concerns that when the driver has no control of the vehicle then pedestrians’ trust would significantly decrease (Stanciu et al., 2017), which in turn will lead to misinterpretation of vehicle’s intent (Habibovic and Davidsson, 2012). A further detailed discussion on communication needs and challenges for self-driving vehicles is discussed in Section 2.2.

2.2 EMBEDDING SOCIAL CAPABILITIES IN FUTURE VEHICLES

The mutual understanding of each other’s intent is crucial for safe interactions between self-driving vehicles and pedestrians (Klien et al., 2004). Negotiation by vehicles is not possible without social capabilities in vehicles, and the major concern is their intent communication to other road users. In self-driving vehicles, the major channel for intent communication – the driver – is lost, thereby creating a communication gap between them and pedestrians. The communication gap and inattention between pedestrians and vehicles are the two major concerns in the design of future vehicles (Rasouli, Kotseruba, and Tsotsos, 2018). Communication needs will change with self-driving vehicles. It is crucial that the communication interface is designed carefully (Bunz et al., 2016), including a balance between how, when, and what to communicate (Habibovic, 2018). The following review provides a further discussion on this issue.
2.2 Embedding Social Capabilities in Future Vehicles

2.2.1 Social contexts in vehicle design

In order to gain insights into pedestrians’ trust towards future self-driving cars, social scientists are studying pedestrians’ action and reaction towards these vehicles in different traffic situations (Keferböck and Rieger, 2015; Lagstrom and Lundgren, 2015; Sucha, 2014). The primary research focus in social interaction context has been on developing and testing different modalities of communication. For instance, a team of researchers at Nissan is focusing on integrating the understanding of social interaction contexts in their autonomous vehicle design (Vinkhuyzen and Cefkin, 2016). The Nissan team introduced their concept car which uses an array of LED lights around the vehicle to alert surrounding road users. The different lighting patterns and colors indicate the level of alert to the pedestrians and whether the vehicle intends to yield/not yield to the pedestrians. In addition, a vehicle interface to display courteous messages, such as “After you!”, to pedestrians on the vehicle’s front windshield is also proposed (Nissan, 2015). The use of external displays for vehicle-pedestrian communication has been suggested in other studies as well (Mahadevan, Somanath, and Sharlin, 2018; Urmson et al., 2015; Zimmermann and Wettach, 2017). Such displays can be used to broadcast informative messages to pedestrians such as speed of the vehicle (Clamann, Aubert, and Cummings, 2017), yielding intention of the vehicle (Matthews, Chowdhary, and Kieson, 2017), or graphics suggesting an action to pedestrians (Clamann, Aubert, and Cummings, 2017; Daimler, 2014).

AutonoMI5 by Graziano (2014), an LED array display on the vehicle for communicating with pedestrians, is another example of an external display for vehicles in which LED array lights up to acknowledge that the pedestrian has been detected. Moreover, when the pedestrian begins to cross in front of the vehicle, the array lights up relative to the pedestrian’s position in the crosswalk to assure that the vehicle knows about their motion. In addition to LED display, other studies suggest using a combination of various other modalities including visual displays and audible warnings to increase the functionalities of a vehicle communication system (Florentine et al., 2016; Siripanich, 2017).

Google’s efforts in this direction are indicated in one of their patents, involving signage and audible warnings to notify the intent of the vehicle (Urmson et al., 2015). The Google team integrated flashing signage on the vehicle door to inform the pedestrians not to cross in front of them. They also added audible warnings, mimicking the characteristics of conventional vehicles, to alert the pedestrians – such as honking like a patient driver, and in other cases beeping while swerving or reversing through the lane.

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5 Autonomous Mobility Interface
At the 2015 international CES event, Mercedes demonstrated their interactive zebra crossing concept vehicle that projects a crosswalk in front of the pedestrian to cross the road, along with light notifications (Mercedes-Benz, 2015). Similar concept was proposed by BMW, and later Mitsubishi also revealed a concept where vehicle motion direction is projected onto the road surface (Mitsubishi, 2015).

Earlier in 2012, Massachusetts Institute of Technology (MIT) researchers came up with a biomimetic vehicle-pedestrian communication system named AEVITA (Pennycooke, 2012). Their system relied on various sensors to express recognition of pedestrians by the vehicle combined with a module to communicate vehicle’s intent. However, their in-campus study does not guarantee positive results in real-life settings, and the authors further clarify that their communication protocols may need to be fine-tuned with more robust testing.

The above different concepts of vehicle interface for communication with the pedestrians provides a way to communicate the vehicle’s intent, however such interfaces do not engage vehicle in a two-way communication with the pedestrians. Yet another social challenge for vehicles is decoding and reacting to the dynamic cues from its environment, for example, how will they react to the nod or wave by the pedestrians in complex traffic conditions. Till now, Google’s driverless vehicles are capable of detecting cyclist’s hand signals (the conventions followed in North America) (Kretzschmar and Zhu, 2015). There are few other works related to traffic hand controller’s gesture recognition (Delp and Caveney, 2016; Guo, Tang, and Zhu, 2015; Tao and Ben, 2010). However, a number of questions arise when related to cultural differences in traffic interactions, such as whether the language of traffic, including these conventions, are universal is not clear. Chapter 3 in this thesis investigates this problem in detail.

Human-robot multi-modal interaction has been investigated in literature where machines can be trained to respond through gestures and facial expressions (Bremner and Leonards, 2016; Han, Lin, and Song, 2013; Wu et al., 2009). The concept of robotic eyes is also introduced in the robotics literature (Fussell, Kraut, and Siegel, 2000; Onuki et al., 2013) but these designs are limited by their application context and cannot independently be involved in non-verbal communication with the humans. A similar concept of human-like eyes is proposed for the vehicles as well (Chang et al., 2017; Pennycooke, 2012). For example, Pennycooke (2012) claimed to detect the gaze of pedestrians and proposed a moving-eyes approach by vehicle establishing virtual eye contact with pedestrians. The moving-eyes of vehicles were generated with the vehicle’s rotating front lights to give an impression of eyes of the vehicle. In addition to these features, the use of robotic hands to perform gestures is also recommended to be

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6 CES is an international Consumer Electronics Conference – the global stage where next-generation innovations are introduced to the marketplace (https://www.ces.tech/)
a part of future vehicles in another study (Mahadevan, Somanath, and Sharlin, 2018). Some researchers also suggest replacing a human driver with a humanoid robot in the driver seat to perform human-like gestures during communication (Mirnig et al., 2017). Nevertheless, the effectiveness of such interaction modalities is not clear in the above studies, also different prototypes have not been tested and validated in actual vehicle-pedestrian interaction scenarios.

2.2.2 Reviewing communication challenges

Industrial efforts in embedding social capabilities in future vehicles are evident from the above review, but implementing them in real-life settings requires more attention. For instance, in some situations, vehicle notifications can be perceived as misleading to pedestrians (Andersson, 2017). In this section, we discuss the pedestrians’ perceived effectiveness of different modes of intent communication by vehicle.

Few studies show that external communication interface for vehicles such as intent displays will improve the experience of pedestrians during interaction with vehicles. One such study by Matthews, Chowdhary, and Kieson (2017) used a controlled golf cart to measure the effectiveness of using an intent display in communication with pedestrians. In their experiments, pedestrians encountered both types of vehicles – with and without an intent display. It was observed that there was 38% improvement in resolving conflicts when the vehicle communicated with an intent display. This study further concluded that pedestrians’ experience can be further improved if they have prior knowledge about the vehicle’s communication mechanisms. Other related studies also support similar observations (Zimmermann and Wettach, 2017) and indicate that an effective communication channel is essential to increase pedestrians’ trust towards the self-driving vehicles.

In contrast, few other studies do not agree to the above observations and argue over the effectiveness of visual intent displays. For instance, Pennycooke (2017) conducted experiments with a hidden driver in the vehicle so that the vehicle appears to drive autonomously. The vehicle was equipped with the display mounted on the roof displaying the message “Safe to cross”. Compared to pedestrians’ initial resistance to cross in front of the test vehicle (autonomous), the results show that there was no significant improvement in pedestrians’ crossing decisions when they encountered the vehicle with an intent display. More specific reason for this observation was revealed in the post-questionnaire of this study – the lack of pedestrians’ trust for autonomous driving. These results can be further linked to pedestrians’ reaction times which increased due to interpreting messages from the external interface, and also the visibility of the displays from large distances. A similar experiment by Clamann, Aubert,
and Cummings (2017), they tried to improvise the above experiment and tested with large LCD displays of intent graphics on the vehicle to rule out the visibility issues. Their conclusions suggested that only a few participants had an actual effective experience with interfaces, while other participants reported that they ignored the displays and relied on their safety intuitions. Further, they found that pedestrians' decision-making time increased in the presence of intent displays. Clamann, Aubert, and Cummings (2017) further emphasized that in any case, vehicle’s speed and distance are still significant parameters in pedestrians’ crossing decisions.

In the context of autonomous driving, other modalities of communication with pedestrians are also investigated. Chang et al. (2017) demonstrated the use of moving eyes installed at the front of the vehicles for the interaction with pedestrians in a virtual reality environment. The majority of the participants in this study reported that their decision-making was effective in the presence of mechanical eyes on the vehicle, while the response was outstanding when vehicles’ eyes looked directly to the pedestrians. The evaluation of this study, however, was limited to a few participants in a virtual reality environment where risks involved were minimal.

Mahadevan, Somanath, and Sharlin (2018) extended the above experiment design and further included audio, visual, and physical cues (such as an actuated hand) in their vehicle-pedestrian interaction test setup. The multi-modal approach in the design of communication interface for vehicles in this experiment provided a better understanding of the usability of different communication modalities. For example, participants in their study appreciated the use of LED strips as visual cues for intent communication, however, highlighted its non-applicability to color blind or visually impaired people. Audio feedback from the vehicle could help pedestrians but at the same time, audio messages from multiple driverless vehicles will not work well. On the other hand, physical cues proved to be a clear form of communication to the pedestrians, while other cues such as vehicle motion remain to be a convenient mode for pedestrians in terms of interpretation. However this study is limited by the number of participants (only 10) involved in their experiments, and all of them exhibited a North American road culture. This study further suggests the cultural differences in physical cues will be a challenge in designing communication interface for vehicles.

Apart from above approaches, communication by implicit cues involving vehicle motion patterns is also emphasized by other studies. For example, Beggiato et al. (2017) studied different braking actions by vehicle to communicate its yielding intentions to the pedestrians. It was found that sudden changes in the vehicle's speed caused pedestrian discomfort in traffic. In another similar study, it was also found that pedestrians often perceive sudden speeding up or braking by a
vehicle as an erratic behavior which confuses the pedestrians (Zimmermann and Wettach, 2017). These findings imply that interpretation of the vehicle motion varies among pedestrians, and is often influenced by demographic factors such as pedestrians’ personalities, and traffic situations. Pedestrian behavior will be further discussed in detail in Section 2.3. Overall, based on the available findings it seems that a multi-modal design of communication interface for self-driving vehicles can reduce the communication gap between pedestrians and vehicles which is necessary especially during negotiation situations.

2.2.3 Vehicle-to-Pedestrian (V2P) communication

So far I discussed external displays as potential communication channels between pedestrians and vehicles, and the associated communication challenges with them as observed in various studies. Next, I further investigate other practical solutions for intent communication among vehicles and pedestrians.

One way of direct and efficient information interaction is through radio communication technology. Short-range communication with vehicles is possible by exchanging information via radio signals, while even wide area communication is possible with a cellular network or satellite communication. Recently, there has been particular attention in developing Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication technology (Cheng et al., 2014; Hobert et al., 2015). Their benefits involve the real-time exchange of precise traffic information including each other’s precise speed and location information, which ultimately helps in reducing inter-vehicle collisions and traffic congestion (Narla, 2013). The extension of this technology for communication with pedestrians – called as Vehicle-to-Pedestrian (V2P) communication – has also been investigated, yet is relatively understudied. Related solutions rely on sensors such as camera, lasers, or wireless network components embedded in both vehicles and pedestrians. For pedestrians, the most efficient and general V2P communication interface solution is a smartphone equipped with the required sensors for V2P communication functionalities.

Earlier in 2013, a Honda R&D group demonstrated Dedicated Short Range Communications (DSRC) technology enabled V2P communication (Cunningham, 2013). Their vehicle-to-pedestrian (V2P) technology used cooperative communication between a pedestrian’s DSRC enabled smartphone and nearby vehicles. They also demonstrated that such a system can be used to provide potential collision alerts to pedestrians through high-volume beep and a warning on the screen of their smartphone. On the other hand, their system also alerts the vehicle through in-vehicle displays. In another similar work Hussein et al. (2016) proposed the use of a smartphone application that broadcasts the heading and location information of the pedestrian, and
also receives similar information of nearby vehicles. Using this information, the application displays the collision-related warning signals to the pedestrians in their smartphones. Apart from smartphone notifications, another option explored by researchers is wearable sensor technology for pedestrians to receive warning signals from vehicles (Gordon et al., 2016).

V2P technology seems to be promising however it also raises a number of concerns among pedestrians. Surveys show that a large number of pedestrians are unwilling to use such applications fearing that these shift the responsibility of potential accidents to pedestrians (McLeod, 2014). Another major concern is privacy issues associated with sharing road users’ personal information (Schmidt, Philipsen, and Ziefle, 2015). Other issues related to the performance of this technology includes channel congestion in dense traffic and communication delay or latency issues (Anaya et al., 2014). A more detailed review of the effectiveness of V2P communication technology to resolve conflicts in traffic will be discussed in Section 2.5.

2.2.4 Other practical solutions - Smart roads

Smart roads concept, enabled by Vehicle-to-Infrastructure (V2I) communications, is another promising technology that may facilitate situation awareness among self-driving vehicles and other road users. Short-range communication technologies like V2V and V2P works better when there are a number of nearby vehicles which can propagate awareness information from one vehicle to another vehicle (or pedestrian). However, if roads can also communicate information then vehicles and pedestrians can even see the situation far away from their location (such as an emergency situation or a potentially colliding swerving vehicle) and hence can act accordingly. Recently, smart road concepts have been gaining popularity among transport planners, exploring robust infrastructure planning to transmit the intentions and whereabouts of the road users in real-time. There might be situations when a vehicle’s intent display and warnings may get ignored by distracted pedestrians. In such cases, smart roads can play a role to inform all road users about the potential threats (Sieß et al., 2015a) using visual and sound effects, or in other situations alert a number of distracted road users with a common interface like alert projections on the road (Sieß et al., 2015b).

One such example is Hybrid City Lighting project which suggests a vehicle-warning system (Sieß et al., 2015a). When this system detects any pedestrian who is not yet in the view of the vehicle and is trying to cross the street, the system projects danger lights in the form of circles in the pedestrian’s vicinity to warn oncoming vehicles about the expected danger at an early stage. This way, the sensors on road in conjunction with information from road users can provide an early
information of the level of imminent danger. Moreover, the warning lights projected on road as concentric circles appear more luminescent depending on how acute the danger is, for example, they start blinking if danger is high, and if the pedestrian stops then circles fade out.

Infrastructure design initiatives for pedestrian-friendly communication have been recently demonstrated by the Umbrellium group, and the Studio Roosegaarde design lab. The former group showcased an interactive crossing concept – a projected crosswalk on road for pedestrians which reacts dynamically in real time prioritizing pedestrians’ safety (Umbrellium, 2017). For example, the width of the projected crosswalk is automatically increased if there are a number of pedestrians crossing at the same time. Moreover, if a distracted pedestrian is detected then a warning pattern of lights is projected around them to fill their field of vision and alert the nearby vehicles about the risk to such pedestrians. Similarly, as a part of the Smart Highway project, Studio Roosegaarde implemented the glowing Van Gogh7 path highlighting traversal paths for cyclists and pedestrians, and a similar concept for highlighting boundaries of highways during night for the vehicles (Roosegaarde, 2015).

Nevertheless, all the above communication solutions between pedestrians and vehicles only provide situation awareness and intent communication of a party. However, none of these solutions guarantee conflict resolution among road users as these solutions do not provide a way to reach an agreement and match the intentions of different road users. Not only the communication solutions between self-driving vehicles and pedestrians, but also negotiation capabilities of a vehicle to reach an agreement (in their intentions) with the pedestrian will allow them to reduce their crossing conflicts, as this thesis will show (Chapter 4).

2.3 Insights on Pedestrians Road-Crossing Behaviors

The pedestrians’ road-crossing behaviors are well studied, however, related studies in the context of autonomous driving are limited. The pedestrians’ perceived risk in presence of self-driving vehicles may vary depending on demographic factors such as age and gender (Deb et al., 2017; Hulse, Xie, and Galea, 2018). Not only demographic factors, but also different types of social information from the environment influence their crossing decisions. Apart from these factors, other factors like group size and social norms influence the risk-taking behaviors of pedestrians. Moving away from the role of vehicles’ communication channels and intent displays in pedestrians’ behaviors, this section further provides a detailed review on the in-

7 Read more about Van Gogh path here: https://www.studioroosegaarde.net/project/van-gogh-path
fluence of above factors in pedestrians’ behaviors, and their role in vehicle-pedestrian negotiations.

2.3.1 Perception of safe gap

Decision making while crossing is often influenced by the cognitive abilities of the pedestrians to perceive a safe gap. This safe gap is a perception of individuals rather than a general measure. The pedestrians have a tendency to take risks if they have the ability to cross quickly, which suggests that age has an impact on their crossing decisions. For instance, children lack the perception of safe gaps and are found to ignore rules more easily compared to adults (Demetre et al., 1992; Schmidt and Färber, 2009). The lack of a safe gap perception makes children’s behavior more varied, and often difficult to predict (Clay, 1995; Holland and Hill, 2007). Similarly, older people with reduced cognitive abilities take some time to perceive their surroundings and often show a cautionary behavior while crossing (Harrell, 1991; Oxley et al., 1997). As a result, they take more time in assessing the traffic situation before crossing (Rasouli, Kotseruba, and Tsotsos, 2017), and are much slower in walking compared to young pedestrians (Ishaque and Noland, 2008).

Moreover, in few studies it is argued that the perception of a safe gap also depends on the gender of pedestrians (Heimstra, Nichols, and Martin, 1969; Moore, 1953). Existing studies on pedestrians’ behaviors show that female pedestrians, in general, are more cautious than male pedestrians while crossing (Heimstra, Nichols, and Martin, 1969; Holland and Hill, 2007). Female pedestrians tend to take less risk and usually demonstrate a higher level of compliance with the traffic laws (Jacobs and Wilson, 1967; Tom and Granié, 2011). As such the reported frequency of unsafe crossing incidents is higher among male pedestrians compared to female pedestrians. However, other studies further argue that the reason for varied behaviors among different genders is mainly due to the differences in their beliefs, motives, and also situational factors (Yagil, 2000).

The analyses conducted by Yagil (2000) show that crossing decisions by male pedestrians are generally predicted on the basis of their perceived benefits of obeying the laws (normative motive); for female pedestrians, however, the crossing behavior is predicted by their perceived danger of crossing (instrumental motive). Another similar study by Tom and Granié (2011) focused on analyzing pedestrians’ patterns of visual search in their surroundings before taking a decision to cross. Their study showed gender-specific differences in crossing decisions related to the differences in their perceived situational factors. For instance, their study showed that male pedestrians predict their crossing action based on the action by vehicle, however, female pedestrians pay more attention to factors such as road structure, traf-
2.3 Insights on Pedestrians Road-Crossing Behaviors

Pedestrians, before crossing. However, in the previous study by Yagil (2000), no significant differences were observed in the behavior of male and female pedestrians with regard to situational factors (i.e. the effect of traffic volume, darkness or bad weather and presence of other pedestrians).

Nevertheless, the implications of various studies suggest that the factors influencing pedestrians’ behaviors are not limited to age and gender but also extend to individual visual perception of objects around them. For example, moving pedestrians have a better perception of the safe gap (in terms of vehicular speed, and distance) compared to standing or waiting pedestrians; the latter ones are willing to wait for approaching vehicle while walking pedestrians have a better estimation of risk to act accordingly (Oudejans et al., 1996).

2.3.2 Social information

Furthermore, pedestrians’ decision-making process before crossing involves the integration of multiple sources of information – the social information which they perceive through their environment. The environment factors influencing their behaviors include the vehicular traffic, infrastructure such as street lights or road markings, and the presence of other pedestrians on road. For instance, pedestrians are more likely to stop or wait at the uncontrolled crossing if the vehicle is approaching at a higher speed. But this decision might be affected by the presence of a crowd as pedestrians tend to take risks because of their tendency to follow the crowd. In addition, pedestrians’ crossing speeds are also often affected by road structures. This is evident from the study by Crompton (1979) who analysed and reported pedestrian crossing speeds at zebra crossings (1.49 m/s), and pelican crossings (1.74 m/s). The increased pedestrians’ speeds at pelican crossings suggest that different types of road markings give different perceptions of safety to pedestrians. The impact of above factors on the road crossing behavior of pedestrians are discussed more in detail below.

2.3.2.1 Effect of vehicular traffic

Previous studies considering the role of social factors in pedestrians crossing behaviors analyze their perception of a safe gap in a subjective manner (DiPietro and King, 1970; Harrell and Bereska, 1992; Schmidt and Färber, 2009; Wang et al., 2010). However, there are also studies which focus on analyzing the gap acceptance of pedestrians with respect to the dynamic factors associated with the approaching vehicles – such as the speed of the vehicle, and its direction and distance from the pedestrian (Lobjois and Cavallo, 2007). Their behavior is also affected by the number of vehicles approaching towards them; for instance, in one of the study it was observed that pedestrians often
restrict their crossing movement when they encounter a large number of vehicles (more than three) (Himanen and Kulmala, 1988).

Out of these factors, the effect of vehicles’ speed and distance from pedestrians has been studied together to measure the gap acceptance among pedestrians. The pedestrians’ gap acceptance is usually measured in terms of Time to Collision (TTC), i.e., the time required for the vehicle to hit the pedestrian with its current speed (Das, Manski, and Manuszak, 2005; Du et al., 2013; Rasouli, Kotseruba, and Tsotsos, 2017). In terms of this measure, the average pedestrian gap acceptance reported in the literature is between 3-7s (DiPietro and King, 1970; Schmidt and Färber, 2009), i.e. pedestrians do not generally accept TTC below 3s but feel safe to cross when it is more than 7s. This gap acceptance measure, however, varies among individual pedestrians depending on demographics and cultures, which aligns with the observations in previous studies (Schmidt and Färber, 2009).

Furthermore, the pedestrians’ ability to estimate vehicle speed and distance influence the way they react to it. With higher vehicle speeds, pedestrians find it difficult to estimate the approaching vehicle’s speed and often rely on vehicle’s distance for their crossing judgments (Clay, 1995). This is also evident from one of the studies by Sun et al. (2015) showing that pedestrians were able to correctly (or closely) estimate the speed of the vehicle when it was moving below 45km/h, but they were better in judging the vehicle’s distance with vehicle speeds up to 65km/h.

Apart from the speed and distance of the vehicle, other characteristics of vehicles such as vehicle size and type have also been observed to influence the pedestrian’s behavior. Das, Manski, and Manuszak (2005) show that pedestrians confronted with large heavy duty vehicles are more resistant to crossing compared to a small passenger vehicle. Another study reveals that it is hard for pedestrians to predict the speed and distance of large or heavy-duty vehicles (Caird and Hancock, 1994). Also, the type of vehicle has an impact on the waiting times of pedestrians, for example, it is observed that pedestrians have better safe gap judgment and lesser waiting times for motorcycles and vans compared to commercial vehicles (Caird and Hancock, 1994; Hamed, 2001).

The above review suggests that physical constraints between vehicles and pedestrians influence the crossing intentions of pedestrians. However, current literature do not reflect the impact of these factors, including pedestrian’s crossing intentions, on the response of drivers in those situations. Furthermore, the factors involved in achieving a mutual agreement among drivers and pedestrians on a crossing decision is also not studied. This problem is identified as a negotiation problem in this thesis, Chapter 4 describes the negotiation process and strategies between a vehicle and a pedestrian based on physical constraints between them.
2.3.2.2 Effect of road infrastructure

Regulated road infrastructure, including pedestrian street lights and marked road crossings, affects the way pedestrians behave in traffic (Ceder, 1979; Moore, 1953; Teknomo, 2006). The traffic infrastructure has been improved over time to reduce the accident risks (Burstedde et al., 2001), however, rules compliance by road users is not always guaranteed (Keegan and O'Mahony, 2003; Mullen, Cooper, and Driskell, 1990; Wang et al., 2009). The pedestrian and vehicle interactions occur even at signalized zones where some pedestrians do not hesitate to cross against the rules of traffic (Lavalette et al., 2009). Different designs have different impacts on traffic flow. For instance, traffic is expected to be regulated at signalized junctions where traffic lights direct the traffic, but the behavior is different at zebra crossings where vehicles generally yield only when pedestrians show their presence (Mortimer, 1973; Sucha, Dostal, and Risser, 2017).

Compared to signalized junctions, pedestrians’ level of attention is higher at unmarked road crossings (Rasouli, Kotseruba, and Tsotsos, 2017); for instance, one related study shows that majority of pedestrians looked out for vehicles at non-signalized junctions while ignoring the same at signalized junctions (Tom and Granié, 2011). Apart from attention, road structure also affects the walking pattern or trajectory of pedestrians. For example, in the previous study, it was also observed that pedestrians are likely to jaywalk at unmarked junctions while they comply with crosswalk structure at signalized junctions. Street widths also have an impact on the pedestrian behaviors (Oudejans et al., 1996); it is observed that pedestrians gap acceptance lowers with wider streets (Chu, Guttenplan, and Baltes, 2004; Schmidt and Färber, 2009) however it also leads to chances of road violations by pedestrians (Lavalette et al., 2009). Pedestrians’ walking speed is also affected by the road structure - they tend to walk fast on crosswalks compared to sidewalks (Moore, 1953; Tian et al., 2013). Moreover, the illumination level on the road also affects the movement of both vehicles and pedestrians. Especially during night time, pedestrians ability to estimate traffic risks decreases so they tend to show a cautious behavior (Harrell, 1991; Sun et al., 2015).

In summary, the above review on pedestrians’ behavior at unregulated roads is different than behaviors at regulated roads and junctions. Also, it is not clear in the above studies whether pedestrians always yield, or always assert their right of way whenever there is a conflict of way with the drivers. This further suggests that pedestrians and drivers are involved in a negotiation at unregulated areas if there is a conflict among them for right of way.
2.3.2.3 Attention and distraction factors

Another interesting behavior of pedestrians is their attention patterns prior to or during the crossing, which can be used to predict the possible pedestrians’ trajectories (Klauer et al., 2005; Underwood et al., 2003). The pedestrians’ attention patterns are consequences of either the social information (as discussed before) they perceive from the environment or their own sources of distractions. The effect of attention has been extensively studied in the context of traffic safety (Barnard et al., 2016; Underwood, 2007). For example, it is generally observed that prior to crossing, the pedestrians tend to establish eye contact with drivers which slow down the drivers (Ren, Jiang, and Wang, 2016). Moreover, their attention patterns also depend on the road infrastructure such as frequency of traffic signals, or the structure of road (Rasouli, Kotseruba, and Tsotsos, 2017); for instance, they are more attentive at an unmarked crossing compared to a regulated crossing (Tom and Granié, 2011). The attention patterns are also studied in terms of the pedestrians’ walking trajectory. A pedestrian, for example, distracted by any electronic device during walking is likely to be inattentive in the traffic. A study by Hyman Jr et al. (2010) showed that distracted pedestrians walk slower than others and their trajectory is hard to predict. The study also emphasizes that pedestrian walking direction plays a role in the way pedestrians make a crossing decision, which is also important for the vehicles to predict their trajectories. These attention cues of pedestrians may be used by drivers to initiate a negotiation during any conflict, but this is not explicitly studied or mentioned in the literature.

2.3.3 Interaction in groups

Among the various social factors influencing pedestrians crossing behaviors, perhaps, group interaction is one of the most common behavior observed in traffic. The scenarios of group formation can be observed in sidewalks closely related to lane formation in public places. In theory, such behavior is described as a self-organized collaborative pattern of motion originating from simple pedestrian interactions (Helbing and Johansson, 2011). Similar theory can be applied to explain the formation of pedestrian queues, waiting or moving to cross.

Through empirical studies, it is observed that one of the reasons for group interactions is the perception of safety. For example, Heimstra, Nichols, and Martin (1969) performed field experiments to analyze crossing behaviors among children, in which more than 80% of the children were found to cross in groups and only a few of them preferred to walk individually. Also, Faria, Krause, and Krause (2010) found that majority of the pedestrians in their experiments tend to start crossing relatively later than other pedestrians in the group, thus assuring less risk involved in the crossing. The group interac-
tion among pedestrians has a social influence on individual pedestrians which indirectly impacts the discipline on roads (Rosenbloom, 2009). For instance, a study by Lefkowitz, Blake, and Mouton (1955) reveals that individuals are more likely to wait with the groups when the traffic signal is red for them, rather than following anyone violating the road rules. However, the former results seem to be biased as the group behavior may vary at unmarked crossings, which is not considered in their experiments.

Other studies, also do not support the above argument which correlates group behavior with rules compliance behavior. For example, Rastogi, Thaniarasu, and Chandra (2010) reported that pedestrians who fall behind in a group of people crossing the road tend to increase their speed to catch up the group flow and quickly cross the road. It was also observed that the primary reason for rule violations by pedestrians was the influence of following the crowd moving ahead of them. Other studies explain that this behavior is a result of any individual’s goals to minimize their waiting times, which comes at the cost of increased risk of injury to them (Faria, Krause, and Krause, 2010).

The group size is another factor that has an impact on the crossing behaviors of both pedestrians and drivers. During crossing as a part of a group, pedestrians are less attentive towards the approaching vehicle and tend to show less cautionary behavior (Sucha, Dostal, and Risser, 2017). Moreover, their gap acceptance also lowers when they move in a group (Harrell, 1991; Schioldborg, 1976; Wang et al., 2010). Even drivers’ yielding behavior increases when the group of pedestrians waiting to cross is more than three (Herwig, 1965; Sun et al., 2003), compared to a single pedestrian waiting. In general, larger group size is related to more waiting time for vehicles as the pedestrian flow is slow in dense groups (Wiedemann, 1974).

The above implications relating to group interaction and its influence on individual pedestrian behaviors can be crucial for self-driving vehicles to understand pedestrians’ intentions, especially when it comes to their crossing decisions. Also, pedestrians’ movement in groups and the size of groups is a cue for the vehicle to estimate its chances of getting an agreement during negotiations for the right of way. The former argument is not present in the existing literature.

In this thesis, Chapter 5 and Chapter 6 will describe vehicle’s negotiation strategies considering the influence of other pedestrians on any pedestrian’s behavior. Simulating pedestrian group behavior is another challenge in demonstrating vehicle-pedestrian negotiations. Pedestrian dynamics simulations are based on certain models, one such example is the social force model. This model provides predictive modeling of pedestrian crowds assuming the influence of environment geometry, and pedestrians’ individual goals to reach the destination encoded as their preferred velocities (Helbing and Molnar,
But this model, and other similar models (Farina et al., 2017), fail to address the issues of individual perceptions, such as waiting behaviors or similar behaviors influenced by other factors. In summary, existing models do not explain (and simulate) negotiating behaviors of pedestrians (and vehicles).

2.3.4 Informal social rules

The above review on pedestrians behaviors suggests that they follow some social rules, yet informal, which play a significant role in decision-making among road users in traffic (Färber, 2016; Wilde, 1980). For example, a pedestrian changing his posture towards the oncoming vehicle, also followed by glancing the approaching vehicle is an informal indication to the vehicle about pedestrian’s intention to cross (Rasouli, Kotseruba, and Tsotsos, 2018). In the former case the driver follows the social norm by yielding to the pedestrian. Another example of social norms is demonstrated by Wilde (1980), who studied the acceptability of road speed limits by the drivers. The driving patterns of majority of drivers in his study indicated deviations from the rule-defined speed limits, about which the author argues that this pattern indicates a different social norm (or informal rules) followed by the drivers. Other studies also argue that social rules influence the acceptability of actions by road users depending on the traffic situations (Evans and Norman, 1998). Wilde (1976) argues that an individual takes decision in traffic in the collective context of behavior of different road participants. This context is characterized by the local social norms, as well as one’s individual expectations and communications on road. Johnston (1973) studied the road accident casualties and argued that following the formal traffic rules does not always guarantee safety in traffic. Furthermore, the former case study on cautious behavior of drivers also illustrated that an individual’s lack of sense for social norms can disturb the entire traffic flow. Wilde (1980) also discussed the concept of the psychological right of way as an influence of social norms. For instance, consider the scenario where a driver wants to pass an unmarked intersection, and legally they have to allow the traffic from right to pass first. However, the observed crossing behaviors of drivers are found to depend on social factors and not necessarily on the laws (Björklund and Åberg, 2005).

Another question is how these informal rules have been developed in traffic. A number of studies relate the influence of local culture on the different behaviors of road users (Clay, 1995; Lindgren et al., 2008; Schmidt and Färber, 2009). Consider the traffic behavior of Western countries compared to Asian countries. The former population is found to be more conservative towards pedestrians, however, the latter population is found to make crossing decisions based on traffic conditions and road structures (Clay, 1995). The common behavior
of local people suggests that culture defines the beliefs and behavior of people, which forms the general set of social norms they usually obey (Lindgren et al., 2008). As such the behaviors in traffic vary among cultures - among different countries, or regions, or even different parts of a country (Björklund and Åberg, 2005).

The above studies describing the influence of social cues on the road user’s behavior and their cooperative actions based on those cues show that informal social rules exist in traffic. It can be further argued that social rules also play a role in describing negotiations between vehicles and pedestrians when they confront each other in a conflicting situation. However, no attempts have been made to systematically describe the social rules of interaction between drivers and pedestrians. Thus, this thesis also conceptualizes the social rules of negotiations between vehicles and pedestrians; negotiation by social rules is investigated in Chapter 5.

2.3.5 Risk-taking behaviors

The pedestrians long waiting times at intersections also have an impact on their crossing decisions. In this context, few studies have focused on analyzing factors related to risk-taking behaviors of pedestrians. For example, Sun et al. (2003) argue that the risk-taking behaviors increase for pedestrians waiting at the crossings for long. In addition, other studies argue that their waiting times and crossing decisions can also be influenced by demographic factors, and their individual personalities (Wang et al., 2010). This is also evident from the discussion in Section 2.3.1 and 2.3.2 that various factors influence the crossing decisions of pedestrians on roads, which influence the risk-taking behaviors of pedestrians.

A conflict situation between drivers and pedestrians largely depends on one’s behavior (pedestrians or drivers) towards others in traffic. The risk of being hit keeps pedestrians typically on the sidewalk, but this behavior varies among places and cultures. For example, pedestrians in Manhattan uphold their right of way at unmarked crosswalks and do not hesitate to cross first; however, in other parts of the United States, pedestrians are found to be more risk-averse due to frequent road rules violations by drivers (Schneider and Sanders, 2015). In crowded spaces, on the contrary, the drivers adjust to the unpredictability of pedestrians and modify their speed and behavior accordingly. When it comes to self-driving vehicles, the trust of pedestrians towards the predictability of vehicle’s behavior is less. Recent human subject studies have shown pedestrians’ unwillingness to cross in front of self-driving vehicle prototypes (Lagstrom and Lundgren, 2015). However, other similar studies report a mix of risk-taking and risk-averse behavior of pedestrians encountering the self-driving vehicle prototypes (Palmeiro et al., 2018).
As discussed earlier, the perception of a safe gap in traffic is individually different (Section 2.3.1). Analytical approaches to risk analysis of pedestrian’s crossing behavior have revealed their interesting waiting time distributions. According to (Li, 2013), the waiting time of a population that consists of both risk-taking and risk-averse pedestrians, in general exhibits a U-shaped distribution. This explains that risk-taking pedestrians become impatient as their waiting time increases. In contrast, the longer waiting risk-averse pedestrians are less likely to cross the street (Li, 2014). However, their hesitation to cross is reduced if their neighbor has started crossing, further suggesting that groups may pursue more unsafe crossing behavior (Faria, Krause, and Krause, 2010). The negotiation concepts presented in this work will be considering different risk-taking behaviors of the pedestrians deduced from the above empirical studies, which is presented in Chapter 6.

2.4 Practical approaches to pedestrians detection and intention estimation

From the point of view of negotiations by vehicle, the methods of pedestrian detection and intention estimation play an important role as future vehicles will rely on those methods for decision-making in traffic. The methods for object detection and recognition has been a focus of research in the robotics literature since past few decades. However studies discussing methods for pedestrian detection and intention estimation by self-driving vehicles are limited. The following review on various pedestrian detection and intention estimation methods highlights the current gaps in those methods, and also emphasizes their potential role in the vehicle-pedestrian negotiations.

2.4.1 Pedestrian detection

Compared to the methods in robotics, there are few challenges identified for algorithms concerning pedestrian detection. Firstly, the high variability in the movement of pedestrians are difficult to analyze, furthermore tracking them from different view angles by a moving vehicle is another challenge (Geronimo et al., 2009). Secondly, the detection methods have to work in a highly dynamic traffic environment which adds further challenges like occlusions, unfavorable lighting conditions, and identifying concerned pedestrians in a complex environment. Thirdly, these methods demand robust performance in terms of reaction times as they are involved in time-critical events on roads.

To overcome these challenges, a number of pedestrian detection methods have been proposed in the past few years (Dollár et al., 2014; Rajaram, Ohn-Bar, and Trivedi, 2015; Tian et al., 2016; Zhang, Benen-
2.4 Practical Approaches to Pedestrians Detection and Intention Estimation

The state-of-the-art methods range from part-based detection algorithms to deal with occlusions (Tian et al., 2015), semantic-classification methods to distinguish pedestrians from background (Tian et al., 2016), and goes further by involving convolution neural networks (CNN) to minimise errors in extracting pedestrians in the scene (Brazil, Yin, and Liu, 2017; Du et al., 2017; Zhang et al., 2016). In the context of autonomous driving, many of these approaches are based on pedestrian detection methods for Advanced Driver Assistance Systems (ADAS). Most of the methods developed for ADAS are a combination of pedestrian detection and collision mitigation mechanisms (Gandhi and Trivedi, 2006; Gandhi and Trivedi, 2007; Gavrila, 2001; Gerónimo, López, and Sappa, 2007; Sun, Bebis, and Miller, 2006).

The major limitation in studying self-driving vehicle design is that the technical literature of self-driving cars is not revealed by the industry. However, it is evident from the collision avoidance and navigation mechanisms in robotics that the focus is on the general context of human safety and therefore machines are programmed for safe mobility (Gandhi and Trivedi, 2007; Geronimo et al., 2009; Hamid et al., 2016). Thus, the above review provides further evidence that self-driving vehicles will be conservative towards pedestrians, which is the premise of the work presented in this thesis.

2.4.2 Intention estimation methods

In the context of autonomous driving, the major challenge for vehicles is to estimate the behavior of moving objects and humans around them. The intention estimation techniques for vehicles have been studied for predicting the behavior of surrounding vehicles (Laugier et al., 2011; Li et al., 2016; Molchanov et al., 2015; Ohn-Bar et al., 2014). Similarly, methods for predicting pedestrians’ intentions (Köhler et al., 2012; Kooij, Schneider, and Gavrila, 2014), or intentions of both nearby drivers and pedestrians (Bahram et al., 2016; Phan et al., 2014), have been a focus of research in the past few decades. The major challenge for these methods is to deal with the uncertainty in the behaviors in traffic and reduce the risks of any potential conflicts. In a connected ecosystem where all vehicles are connected, a self-driving vehicle can deal with the intention uncertainties of other vehicles in the shared space through V2V cooperative control operations (Bertini et al., 2016). In fact, the precise knowledge of other vehicle’s parameters and signal timings at signalised junctions can provide an optimal speed profile for every vehicle (Katsaros et al., 2011) to optimize their overall trip in order to maximize the fuel efficiency (Asadi and Vahidi, 2011).

However, the vehicle will also be confronted with human road users, and it has to deal with their uncertain behavior, for exam-
ple, a pedestrian suddenly changing his direction to cross the street. The latter agile behavior is, however, challenging to predict. One way to model such behaviors is by using probabilistic models. There are frameworks in decision theory to model the uncertainty in human behavior. For example, POMDP (Partially Observable Markov Decision Processes) formulation provides a probabilistic model of predicting behaviors which integrates uncertainty in human intention as a hidden state in the decision process (Broz, 2008; Kaelbling, Littman, and Cassandra, 1998). This approach has been used to develop the human driver’s behavior prediction model. For instance, Song, Xiong, and Chen (2016) used POMDP to model uncertain intentions of human-driven vehicles at an uncontrolled intersection and proposed an autonomous driving decision-making method for vehicles. In another related work, Wei, Dolan, and Litkouhi (2013) proposed Bayesian probabilistic driving intention estimator which allows autonomous vehicles to cooperate with human-driven vehicles while merging at freeways. However, their application is limited to in-lane driving. In the above studies, the observables are the position and acceleration of the vehicle. These observables are good enough to predict the driver’s intentions as the vehicle’s motion for the next few seconds can be precisely mapped with these parameters. However, in the case of pedestrians, similar estimation methodology may involve large uncertainty as their intentions may change significantly in the next moment.

Further in this section, we only focus on pedestrian intention estimation methods in the context of self-driving vehicles. Typically, these algorithms are similar to movement tracking systems in robotics, i.e., one’s intention can be predicted by analyzing their past and current trajectories. Related work in this field relies on the available information about pedestrians motion, which is used to predict their possible movements. Majority of these methods consider dynamics of the pedestrians such as their speed and position, to estimate their intentions (Schulz and Stiefelhagen, 2015). In addition, few methods also take into account physical constraints such as their distance from the vehicle and moving direction, situational awareness factors such as their head orientation (Brouwer, Kloeden, and Stiller, 2016), and other social contexts such as their distance from the curb, group size, and infrastructure (Brouwer, Kloeden, and Stiller, 2016; Hashimoto et al., 2015). A detailed review on different methods taking into account these factors is discussed next.

2.4.3 Vision-based intention estimation methods

In robotics, particularly in the field of human recognition and tracking, intention estimation is considered as a trajectory extrapolation problem (Bai et al., 2015; Bandyopadhyay et al., 2013; Long, Liu, and Pan, 2017). Related work on multi-person pose detection methods
is relevant to self-driving vehicles as well. Tracking across multiple frames should provide an estimate of future trajectories of pedestrians (Xiao, Wu, and Wei, 2018). Vision-based intention estimation methods, for example, video tracking and analysis (Benenson et al., 2014; Enzweiler and Gavrila, 2009), involve generally a three-step process – image acquisition, extracting features, and the classification process (Brunetti et al., 2018). The primary observations in these methods are the changes in the position, speed and orientation of pedestrians in either two-dimensional (Goldhammer et al., 2014; Mögelmose, Trivedi, and Møeslund, 2015) or three-dimensional (Quintero et al., 2014) video acquisition configurations. Multi-sensor systems allow to capture motion-specific information of pedestrians in a scene (Mobus and Kolbe, 2004; Sachs et al., 2008; Wang et al., 2007), while machine learning techniques can be used to infer their intentions from the available past and current data (Brunetti et al., 2018; Krizhevsky, Sutskever, and Hinton, 2012; Tomè et al., 2016).

Recently deep learning methodologies and, in particular, convolutional neural networks (CNN) have gained attention for pedestrian intention estimation. For instance, Čermák and Angelova (2017) built a neural network model to identify pedestrians crossing intention as either stop or go, based on the current position of pedestrians. Another variation of this model takes into account the past few steps taken by the pedestrian along with pedestrian’s current location to identify their probable direction of movement (Köhler et al., 2015). Another approach in the classification of behaviors is a State Vector Machines (SVM) algorithm, which classifies pedestrian body postures as ‘not willing to cross’ or ‘about to cross’ (Köhler et al., 2012). In this study, the background subtraction method is used to extract pedestrian postures in successive image frames. A superimposition of postures in consecutive frames gives the final image to classify whether the pedestrian is going to cross (Köhler et al., 2013, 2015).

Additionally, other models considered pedestrian’s speed and their distance from the vehicle and curb to infer their crossing decision using an artificial recurrent neural network (RNN) (Völz et al., 2015). In an extension of this experiment, the authors also used an awareness factor and argued that inclusion of such factors improved the estimation accuracy by identifying pedestrians who are less likely to cross if they look towards the vehicle (Kooij et al., 2014; Völz et al., 2016). This highlights the fact that if intention estimation is done using only trajectory information, then data-driven machine learning methods are vulnerable to false predictions. For example, a pedestrian walking alongside the road may suddenly change his direction while based on the motion history data current approach may not identify their crossing intention (Schmidt and Färber, 2009).
2.4.4 Social contexts in intention estimation

Social context, such as pedestrians’ head orientation relative to the vehicle, is also utilized for intention estimation in few other methods (Hariyono et al., 2016; Kooij et al., 2014; Kwak, Ko, and Nam, 2017). Other factors, such as social forces in the form of pedestrians repulsion and attraction with other pedestrians, have also been studied to predict future behaviors of pedestrians. Social forces are identified as relationships between pedestrians which increase the likelihood of collisions among pedestrians (Pellegrini et al., 2009). These type of forces can be identified in image sequences capturing pedestrians walking close to each other for a reasonable amount of time, which can be used to predict their collective movements (Madrigal, Hayet, and Lerasle, 2014).

Another social factor in intention estimation problem is the influence of various objects in the scene. For example, the presence of phone co-located with pedestrian pose provides the level of pedestrian’s engagement in the street (Rangesh and Trivedi, 2018), which is an indication that pedestrian is likely to have an inattentive crossing intention. Similarly, other contextual factors such as road structure, traffic signals, and road markings also influence the accuracy of intention estimation in the model. For instance, Rasouli, Kotseruba, and Tsotsos (2017) demonstrated the use of two neural network models, one for social context elements and other for pedestrian’s posture, to estimate their crossing intentions. The scores from both models were used to classify the intention of the pedestrians. It was reported that the intention estimation accuracy improved by using contextual factors in the process. In a similar study, Schneemann and Heinemann (2016) used information about road structure including street zones, sidewalks, and curb area to form an image descriptor, and developed a SVM model to assess the pedestrians’ likelihood of crossing. In this case also the estimation accuracy is reported to be improved.

By discussions so far, most of the techniques for pedestrian intention estimation relies on machine learning techniques which have proven their application in classification and prediction of different kinds of behaviors. The performance of these methods is reported in terms of the classification or estimation accuracy, which is the most common metric adopted since the development of these methods (Provost, Fawcett, and Kohavi, 1998). This metric – estimation accuracy that pedestrian will yield – is used as an input in the proposed negotiation model in Chapter 4.

2.5 Conflict resolution by self-driving vehicles

As discussed so far the social behavior of a self-driving vehicle depends on how they will perceive their surroundings which is con-
strained by their sensing capabilities. Communication is necessary among traffic participants to share each other’s intentions in order to avoid any conflicting situation. However, conflicts exist even when there is communication as there are chances of uncertainties in perception of the other’s behavior (Elhenawy et al., 2015).

Cooperative behavior enabled by vehicle-to-vehicle (V2V) and vehicle-to-pedestrians communication (V2P) should overcome deficits of autonomous decision making. Cooperative behavior, however, depends on many factors such as identifying the other interacting agent, estimating each other’s motion intentions, and exchanging accurate behavioral information about each other for decision making. In the following section, various conflict resolution mechanisms for autonomous decision-making for self-driving vehicles are investigated.

2.5.1 Cooperative behavior with connected vehicles

With existing road infrastructure, the most common form of controlling traffic is either using traffic lights to regulate the traffic flow or traffic rules which are meant to instill road safety (Guberinic,Senborn, and Lazić, 2007). These methods introduce a regulated negotiation in traffic whose efficiency depends on the level of compliance by road users. Moreover, these methods are sometimes inefficient, for example during less busy hours vehicles are required to wait at a stop sign even when there is no traffic from other directions.

To overcome these shortcomings, smart traffic signal control algorithms have been introduced to reduce traffic conflicts using vehicle-to-infrastructure (V2I) communication (Kaths, Papapanagiotou, and Busch, 2015; Pandit et al., 2013). For example, based on the motion information of various vehicles smart traffic lights can adjust signal timings to optimize the flow of vehicles (Xu et al., 2017). This is a form of centralized traffic control mechanism often called as cooperative adaptive cruise control (Zohdy, Kamalanathsharma, and Rakha, 2012) or centralized model predictive control (Murgovski, Campos, and Sjöberg, 2015; Riegger et al., 2016). There are methods which utilize V2I communication technology for scheduling the passing order times for vehicles (Dresner and Stone, 2004, 2005). The advantage of such methods is that vehicles are no more responsible for managing conflicts, as all vehicles are following the integrated scheduling (Bashiri and Fleming, 2017). However, the above conflict-resolution methods entirely rely on a centralized service which can be unsafe if the system is broken.

Connected vehicles use a number of advanced communication technologies to exchange information with road infrastructure (V2I), and even with other vehicles (V2V) and pedestrians (V2P). Communication among connected vehicles can substantially reduce the uncer-
tainty in the perception of other vehicles’ intentions, thus ensuring some degree of cooperation among them and thereby reducing conflicts at intersections. An example of a conflict-resolution method using V2V communication is reservation-based intersection management. According to this method, the vehicles broadcast their claim to pass the intersection first, and the time-slot allocation is done based on their request arrival timestamps (VanMiddlesworth, Dresner, and Stone, 2008). Other similar methods are also introduced considering alternative scheduling options in cases of communication failure (Savic, Schiller, and Papatriantafilou, 2017). However, the applicability of these methods are not confirmed in denser traffic and the above methods do not guarantee a deadlock-free mechanism. Another popular multi-vehicle conflict resolution method is First-Come-First-Serve (FCFS) or priority based intersection management. Using this approach the passing order of vehicles is determined by giving priority to the vehicles based on their anticipated arrival times at the conflict zone (Azimi et al., 2013). The scheduling strategy in this method cannot be adjusted in real time, however other recent methods claim to overcome this problem to some extent (Liu et al., 2018).

In summary, multi-vehicle conflicts at intersections can be resolved through connected automated vehicle technology, however, none of these methods consider pedestrians in the traffic scenario. As such, the efficiency of these methods in improving traffic flow in realistic scenarios is not clear.

2.5.2 Connected vehicles and pedestrians

Applicability of similar technologies (as V2V and V2I) for communicating with pedestrians has also been studied as vehicle-to-pedestrian (V2P) communications (Andreone et al., 2006; David and Flach, 2010; Ohn-Bar and Trivedi, 2016; Sugimoto, Nakamura, and Hashimoto, 2008). However, the efforts are limited in this direction compared to studies in V2V communications. The primary objective of developing V2P technology is to reduce vehicle-pedestrian collisions by communicating early information regarding their position and trajectory. One such example is the Walk-Safe application which uses camera embedded in the smartphone to detect the approaching vehicle (Wang et al., 2012). However, its application is limited by the sensor’s field of view, and also weather and lighting conditions. The pedestrian may carry their smartphone in any manner, and when the camera is facing in random direction then vision-based techniques fail to work. Radio-based communication has the potential to overcome field-of-view problem in vision-based methods. Examples of this approach are Watch-Over and Ko-TAG projects (Andreone et al., 2006; Naujoks et al., 2015; Seeliger et al., 2014). Both these projects utilize radio sig-
nal measurements from the pedestrian’s handheld device to estimate the approximate location of the device. Nonetheless, the scope of these projects is limited to detecting the presence of pedestrian by measuring signal, with no further capabilities to deliver information (Merdrignac, Shagdar, and Nashashibi, 2017).

Another solution is to use wireless communication that allows vehicle sensors to exchange information with pedestrian handheld devices (Liebner, Klanner, and Stiller, 2013). Typically, the communication range of Wi-Fi is much larger compared to the coverage of embedded sensors. In the year 2013, Honda released its concept of V2P communications technology in a specially built handheld device for pedestrians which can communicate over Wi-Fi channel (Cunningham, 2013). However, other researchers argued that their solution would create channel congestion problems in denser traffic (Anaya et al., 2014). Few others proposed to exploit the capabilities of both Wi-Fi and cellular networks to reduce the communication delay (David and Flach, 2010; Sugimoto, Nakamura, and Hashimoto, 2008). This is particularly necessary to the risk of an accident by adopting a centralized communication scheme. For example, Sugimoto, Nakamura, and Hashimoto (2008) proposed a centralized approach based on Wi-Fi and cellular networks communication systems, in which a central controller (e.g. a cellular network tower) can communicate with both vehicles and pedestrians who are not in each other’s line of sight. If there is any anticipated risk, then the controller can redirect the concerned vehicle and pedestrian to directly communicate via the Wi-Fi channel. This method can be effective in reducing accidents but the limitation of this approach is that reliability on central controllers will result in scalability issues.

From the above discussion, it is clear that V2P communication technology can be used to estimate the collision risk and provide early warnings to both vehicles and pedestrians. However, pedestrian safety can only be ensured with these methods if there is no response latency on the pedestrian’s side. Nevertheless, the above approaches only provide cooperative awareness of the possible conflicts and help to avoid them, but do not provide solutions to resolve conflicts if conflicts happen to occur. This argument holds because none of these methods guarantee an agreement of non-conflicting actions among self-driving vehicles and pedestrians. So it is clear that the vehicle-pedestrian negotiation problem is still an open issue. In this regard, previously discussed cooperative intersection management with connected vehicles is a solution for negotiation among vehicles. However, when pedestrians are introduced in the scenario then it becomes a multi-party negotiation problem. To the best of our knowledge this kind of negotiation problem is not investigated in literature.

In summary, this chapter identifies the current gaps in literature in context of the vehicle-pedestrian negotiation problem. Firstly, the
elements of non-verbal communication in traffic is discussed, however it is not clear whether such language in traffic is universal. Secondly, existing studies, both theoretical and practical, focus on analysing and predicting pedestrians’ intentions and are limited to discussions on their specific behaviors, and the influence of various factors on those behaviors. However, there is limited emphasis on identifying the social rules of interactions between vehicles and pedestrians which plays a more important role in influencing the intentions of road users. Thirdly, different communication channels between self-driving vehicles and pedestrians are proposed and discussed, but they only ensure one-way communication of vehicle’s intent. Even the V2P communication technology only provides situation awareness, but the problem of reaching an agreement in traffic is still not resolved. This thesis is an attempt to investigate all these research questions and introduce the first negotiation model between self-driving vehicles and pedestrians.
This chapter is based on the publication “Conventionalized gestures for the interaction of people in traffic with autonomous vehicles” published in the Proceedings of the 9th ACM SIGSPATIAL International Workshop on Computational Transportation Science by Gupta, Vasardani, and Winter (2016). As such, most of the content in this chapter is compiled from this publication. My contribution as a first author in this work includes proposing the research problem and hypothesis; collecting the relevant information and performing analysis; evaluating the hypothesis; and also providing related discussions and conclusions. The entire work was supervised by my supervisor Prof Stephan Winter, and co-supervisor Dr Maria Vasardani, who actively provided their suggestions and feedback at each stage of this research.

3.1 GESTURAL INTERACTION IN TRAFFIC

The role of non-verbal communication among road users in negotiations has already been discussed in Chapter 2. Färber (2016) emphasizes that the language of traffic, especially in negotiation situations, is characterized by informal communications. For instance, specific characteristics on road, yet informal, serve as basis for reasoning about road users’ behaviors – e.g. a driver’s driving behavior is expected to be cautious in presence of children and elderly people on road (Oxley et al., 1997). The presence of emergency vehicles causes the traffic to self-organise to give them a priority. Similarly, certain movement actions of road users are predictable, for example, if a pedestrian is approaching a crosswalk then their body language will apparently make the driver assume that they intend to cross (Rasouli, Kotseruba, and Tsotsos, 2017). Furthermore, one’s body orientation can also describe their direction of movement as “turning left or right” (Kita, 2003). In case of negotiations between vehicles and pedestrians, the language of gestures and body movements is relevant as this form of communication is customary among road users (Färber, 2016). For instance, pedestrians use their hand signals to block the oncoming vehicle, while drivers often move their hand down to signify the following vehicle to slow down. Due to regular interactions in traffic, both drivers and pedestrians are usually familiar with such informal signals and their interpretations in that context. However, the existence of a universal pattern of these gestures in the traffic language cannot be guaranteed. As such, gestures are sometimes difficult to interpret due to cultural variations. For example, the thumbs-up gesture can
be understood as a universal sign of “OK”, but hand gestures used for counting are culturally diverse. If even these elementary gestures are not universal or unambiguous, then a work into the universality of movement gestures is certainly necessary.

3.2 UNIVERSALITY OF GESTURES - PRELIMINARY STUDY

In order to ground further research on some conventionalized human behaviour, this chapter is focused on the study of traffic control officers’ gestures directing the general traffic at road intersections and worksites. In particular, the aim of this research was to catalogue the conventions related to particular tasks and find universal commonalities as well as differences between cultures and regulatory frameworks. This work answers the question whether there is a general and universal language to interact with traffic. If so, then future work can identify elements of this universal language in other road users, and facilitate an understanding between them and self-driving vehicles. Also, understanding these gestures via visual sensors can form the basis for a self-driving vehicle to behave predictably.

3.2.1 Research summary

The hypothesis of this research is that a universally accepted set of gestures can be identified from the rules used by traffic controllers to direct road traffic. This leads to the following research questions:

1. Can the hand signals used by traffic control officers for standard situations such as directing the traffic at 4-way junctions, directing the traffic at emergency spots or road maintenance work areas, or guarding pedestrians at pedestrian crossings, be catalogued and categorized?

2. What are the commonalities and differences between the conventions in different regulatory frameworks?

3. Is there a universally accepted set of gestures for certain intentions?

4. Do traffic control officers use other elements of expressions (like eye gaze, instruction batons) along with hand signals to direct vehicles on the road? What are these situations?

This work addresses the above research questions and catalogues the universal hand signal rules used by traffic controllers at road intersections and worksites. The conventions for these gestures followed in different countries are explored, and then evaluated based on various elements of expressions involved and local agreements of their execution.
The contribution of this research is that it lays the foundation for the understanding of traffic controllers’ gestures by self-driving vehicles, by classifying different hand signal rules and identifying the general language to direct traffic at controlled road sites. Furthermore, elements of these gestures will be found in other road users’ behavior as well, and thus will be part of a broader interaction with self-driving vehicles.

3.2.2 Psychology of gestures

The fundamental human-machine interaction problem is how the interaction among them can be understood and shaped (Goodrich and Schultz, 2007). One of the components in an interaction is a gesture, which is an integral part of a language and is often linked with some semantic content (McNeill, 1992). Kurtenbach and Hulteen (1990) define a gesture as the “motion of the body that contains information”, which can be classified according to their functions and the process of communication (McNeill, 1992; Mulder, 1996; Rime and Schiaratura, 1991). Gestures are often accompanied by speech, but are also studied as signs and signals for human interaction without speech, in which case they are called semaphoric gestures. The term is borrowed from telegraphy by visual signals. Quek et al. (2002) define such gesturing system as a stylized dictionary of static or dynamic hand or arm gestures for signalling. The categorization of non-verbal behaviour by Ekman and Friesen (Ekman and Friesen, 1969) provides five classes of gestures differentiated by their functions as follows: emblems (culturally established agreed-on gestures), illustrators (gestures complementing the verbal message), regulators (gestures accompanying speech to regulate what is being communicated), adaptors (gestures indicating internal states), and affect displays (carrying emotional meaning). The gestures in traffic fall in the category of emblems which have a specific meaning mostly agreed within a culture (Ekman and Friesen, 1969).

3.2.3 Approach

The research problem addressed in this work is targeting the gestures involved in traffic control procedures at road intersections and work-sites. The next section will discuss and compare the hand signal rules which are used to control traffic at road intersections in the following countries – UK, USA, Australia, Germany, India, and China. Traffic officers are also employed at road worksites to warn incoming traffic. The traffic control procedures involving hand gestures at road worksites which are followed in the USA, UK, Australia and British Columbia are also evaluated in this work. The selection of above countries for this research was restricted by traffic codes availability.
The first step in the study of traffic controllers’ hand gestures is to explore the sources which define these hand signal rules. The hand signal rules encoded in the traffic control manual of different states of a country form the representative sample of gestures for that particular country. The comparison between gesture rules in different countries is done by comparing certain attributes of a hand signal, which can be still or in motion. According to kinesics theory of non-verbal communications (Birdwhistell, 1952), the communication involving eye behaviour and head movements shows signs of attention. In this study, the hand signal is classified based on the following attributes: the gestures involved (arm in some static position, arm waving, arm/finger pointing, head movement, eye contact), arm and body position (left/right arm direction, head direction), target traffic direction (front, left, right, behind) and other traffic control devices used (flashlights, reflective sticks, whistles, instruction batons). The above classification of hand signal rules is used to identify the differences and commonalities in gestures involved in directing traffic in different countries.

3.2.4 Traffic manual codes

There is no universal rulebook which states the conventions for traffic controllers’ hand signals. Instead specific instructions manuals are released by concerned authorities of different states. The various sources of this study are discussed here. The UK Highway Code is prepared by Department of Transport and Driver and Vehicle Standards Agency. It contains signal rules used by authorised persons including traffic officers, which applies to all road users in England, Scotland, and Wales. In the USA, the police departments of individual states have published manuals providing the basic techniques of traffic law enforcement. This includes the hand signal rules to control traffic at intersections. In this research, the rules have been compiled from manuals provided by Florida Department of Law Enforcement, Seattle Police Department, Wisconsin Department of Justice and North Carolina Justice Academy. In Australia, the Western Australia Safety Commission has published an easy to read guide to Western Australia Road Traffic Act and Road Traffic Code 2000, which also contains the hand signal rules for directing traffic. The Queensland Department of Transportation conforms to the rules described in the Police Powers and Responsibilities Regulations. The schedule 4 of the Police Powers and Responsibilities Regulations illustrates ways that an officer may give a direction to a driver or pedestrian by hand signals.

The German traffic code is based on Road Traffic Regulations – Straßenverkehrsordnung (StVO, §36 Zeichen und Weisungen der Polizeibeamten). In India, the transport department of individual state regulates the various traffic rules and regulations. The traffic officer’s
### Table 1: Gesture classification for road intersection scenario

<table>
<thead>
<tr>
<th>Command</th>
<th>Country</th>
<th>Gestures involved</th>
<th>Arm and body Position</th>
<th>Target traffic</th>
<th>Traffic control devices used</th>
</tr>
</thead>
</table>
| **Stop** | **UK** | Arm static | 1. Right arm straight up  
2. Left arm extend | 1. Front  
2. Behind | Night time operations |
|         | **USA** | Arm static | 1. Extend the arm to gain attention and then raise hand up towards traffic  
2. Left arm extend | Front | One long blast of whistle |
|         | **Australia** | Arm static | 1. Right arm straight up  
2. Left arm extend | 1. Front  
2. Behind | Traffic wand used in Queensland |
|         | **Germany** | Arm static | Both arms extended | Front & Behind | Night time operations |
|         | **India** | Arm static | 1. Right arm straight up  
2. Left arm extend  
3. Right arm up/left arm extend | 1. Front  
2. Behind | Whistle blow to gain attention of driver |
|         | **China** | Arm static | Left arm straight up | Front | Night time operations |
| **Go** | **UK** | Arm waving and/or head movement | 1. Right arm up and waving  
2. Head sideways and arm waving  
3. Head and waving arm in direction of traffic | 1. Front  
2. Behind  
3. Side | Night time operations |
|         | **USA** | Arm pointing and static | Arm pointing in direction of traffic, then raise palm past centre of the face | Side | Two short blasts of whistle |
|         | **Australia** | Arm waving | Extend one arm and wave another arm in the direction of traffic | Side | Traffic wand used in Queensland |
|         | **Germany** | Arm waving and pointing | One arm pointing in driver’s direction and other arm waving | Side | Night time operations |
|         | **India** | Arm static and waving | 1. Right arm up and waving  
2. Right arm up and left arm waving  
3. Left arm extended and right arm waving | 1. Front  
2. Left  
3. Right | Whistle blow to gain attention of driver |
|         | **China** | Arm static and waving | Both arms extend/one arm waving in direction to proceed | Side | Night time operations |
| **Left turn** | **USA** | Arm pointing | Extend left arm and pointing | Left | Several short blasts of whistle to get attention of driver |
|         | **China** | Arm static and/or waving and head movement | 1. Right arm extends, left arm at rest/waving and head in direction of turn  
2. Left arm extends, right arm at rest and head in direction of turn | 1. Left  
2. Right | Night time operations |
| **Right turn** | **USA** | Arm waving and pointing | 1. Point with extended left arm and then swing arm in left direction  
2. Point with extended right arm and then swing arm in right direction | 1. Left  
2. Right | Several short blasts of whistle to get attention of driver |
|         | **China** | Arm static and head movement | Left arm extends, palm up and head towards traffic | Side | Night time operations |
| **Attention** | **Germany** | Arm static | Right arm straight up | All | Night time operations |
|         | **India** | Arm static | Both arms raised straight up | All | Whistle blow to gain attention of driver |
| **Pullover** | **Australia** | Finger pointing and eye contact | Stand sideways and point to direction | All | Traffic wand used in Queensland |
|         | **China** | Arm pointing and eye contact | Right arm pointing at a place to stop | All | Night time operations |
| **Left turn waiting** | **China** | Arm pointing and head movement | Left arm pointing to wait and head towards traffic | Side | Night time operations |
| **Slow down** | **China** | Arm pointing and head movement | Arm pointing down and head towards traffic | Side | Night time operations |
| **No change** | **China** | Static posture | Stand straight | All | Night time operations |
hand signal rules can be accessed through the concerned state authority’s website, although the same hand signal rules are followed in every state. In China, the traffic control rules are regulated by the Chinese Ministry of Public Security. The Chinese authority has released the hand signal rules encoded in a chart which is available to general public through the government website.

The standards prescribed for traffic control procedures at worksites are different. The general commands and associated hand signal rules at worksites are evaluated in the next section. Section 6E of Manual on Uniform Traffic Control Devices (MUTCD 2009 edition, revised May 2012) states the hand signal rules and control device standards for maintenance work in US highways. In Australia, the worksite traffic control operation and device standards comply with the Australian Standards AS 1742.3-2009 Manual on Uniform Traffic Control Devices (MUTCD). In the UK, the Highway Code is followed which conforms to the laws stated in Traffic Management Act 2004. In British Columbia, the rules for traffic control are stated in Occupational Health and Safety Regulation and the Workers Compensation Act.

The next step is to classify these gestures. The hand gestures are studied from the above sources and classified based on the attributes discussed in the previous section. This leads to the gesture classification listed in Table 1 and Table 2 for road intersection and worksite scenarios respectively.

### 3.2.5 Evaluation

The general commands to control traffic at road intersections are **Stop** and **Go**. Apart from these, the different countries depending on their traffic codes may also follow one or more commands from the following – Right turn, Left turn, Pullover, Attention, Left turn waiting, Slow down, and No change.

The classification reveals that the gesture used to stop traffic is the same in all the countries listed in Table 1, except in Germany where both arms are extended sideways to stop the traffic. This extended arm gesture is used in USA to gain attention of vehicle to be stopped. **Attention** command means all the vehicles must stop. In Germany, it
is implemented by raising one hand straight up (palm facing traffic) whereas in India both the hands are raised to indicate the same. Chinese traffic rules allow one more command – No change which means there is no change in current flow of traffic and is indicated by a static standing posture of traffic controller.

Arm waving gesture is commonly used to move the traffic, where one arm is extended towards the directed traffic and other arm is waved to move the traffic. This gesture is executed with some local variations in different countries. For example, in USA the officer raises his palm past the face centre (static gesture) instead of waving, and other arm is used to point towards the traffic. There is a slight difference in gesture used in India where the officer raises either arm to stop traffic at one side and wave the other arm to move the traffic of the other side. In UK, this gesture also involves the head movement towards the traffic addressed.

Hand signal to allow left turn or right turn is implemented in USA and China, and the gesture for this command is same in both countries except the orientation of palm while extending the arm. In China, the traffic controller uses an additional command – left turn waiting, where officer points at the position where vehicle should wait to take a left turn. The pullover command is used in Australia and China to stop drivers who break the road rules. This is a pointing gesture and requires eye contact with the driver directing to stop at a particular point.

Another important component in these rules is the use of assisted traffic control devices. In USA, use of whistle is extremely important while directing traffic. Traffic wands are used along with hand signal to direct traffic in the state of Queensland, Australia. In other countries, traffic control devices like illuminated batons and reflective sticks are used only during night-time traffic operations.

Next, the traffic management rules in work zones are discussed, which are different from above stated rules at intersections. Flaggers’ advanced warning signs are positioned in the work zone to warn incoming traffic to follow the traffic controller’s signals ahead. The operations to control traffic around worksite areas are found common in traffic codes of different countries. These general commands are Stop, Release, and Slow down. The traffic is directed using SLOW/STOP signs in conjunction with the hand signals while watching the vehicles. There are some equipment changes in the night-time flagging operations. A retro-reflectorized vest along with reflective sticks (or flashlights and flags) are used to gain the attention of the driver.

The hand signal rules defined in Table 2 are compiled from the road traffic codes of the USA, Western Australia, Victoria Australia, UK, and British Columbia, Canada. These rules involve the use of instruction batons along with arm movements, and the execution of these gestures is quite similar in these countries. Most of the state
traffic rules describe that the controller should hold the baton straight, except in UK and Victoria, Australia where the baton is extended at an angle of 45 degrees. In the USA, a flagger can use the red flag to direct traffic in an emergency situation which is not common in other countries. But the general commands and their rules of execution at worksites indicates that an underlying universal language is followed in many states.

3.3 DISCUSSIONS

The differences and commonalities in traffic controllers’ hand signal rules are studied based on the evaluation of various elements present in the gestures involved. These gestures are different for road intersections and worksite traffic control operations. The traffic operations at intersections involve more use of gestural communication with limited use of traffic control assisted devices (such as flashlights, batons, whistles etc.). However, at worksite operations the use of instruction batons that conform to local conventions of traffic standards is necessary along with signalling through hand gestures.

The common instructions to control traffic at road intersections are to stop and move the traffic. Other commands are also listed in the manuals of individual states, which are followed locally. Though some elements of the gestures for particular operations overlap in all the cases, the overall gesture rules are not universal. For example, the most common gesture to indicate a stop command is to raise one of the arms up facing towards the vehicle while the other arm can be extended in parallel. But the German rule requires the extended arms gesture to indicate the same. The lack of universality in gestures for this command can be explained by recurring to affordance theory (Gibson, 1979): the two different gestures simply express two different image schemata, one – raising the arm towards the vehicle – expressing repulse, the other – extending both arms – expressing blockage. This explanation, however, raises the expectation that (a) the gestures for other commands can also be explained by affordance, and thus that (b) despite the lack of universal gestures for certain actions their individual forms can be universally understood (via affordance).

Similarly, arm waving is a common gesture to move the traffic, but there are local variations in the ones used in the USA where traffic is indicated to move using two motions – a pointing gesture to gain attention, followed by a static arm position to move traffic. The rules for certain commands in some countries involve the movement of the head which may not necessarily be present in other countries. These examples confirm that traffic controller rules are not universal, but they are supporting the explanation that any rule is based on embodied affordance.
Generally, worksite operations are regulated with more commonalities between countries than operations at intersections. Also, the classification of hand gestures corresponding to these commands shows more similarities. Few differences are observed in the holding position of a baton. In Victoria, Australia and the UK the baton is tilted at an angle of 45 degrees to make sure that it is visible to the traffic row, but in other countries it is preferred to hold it straight. Nevertheless, in this case the significant overlap in hand gestures can be inferred as a sign of a common underlying language to control worksite operations.

3.4 CONCLUSIONS

The hand signal rules used by traffic controllers for controlling traffic in standard situations such as road intersections and worksites can be catalogued from the sources provided by transport authorities of different states. Research in classification of hand and body movements has contributed to understanding of the psychology of these gestures. The proposed categorization of hand rules provides revelations about the various elements involved in such gestures, which includes arm movement, eye behaviours, body postures and head movements.

For traffic control at worksites the commands are found to be common across the countries, but the gestures involved in these rules exhibit only some similarities. The hand signal rules for traffic control at road intersections vary more broadly among countries, with overlap in gestures followed in some countries, but stark contrasts between groups of countries.

Thus out of the two scenarios considered in this study it can be concluded that significantly similar hand gestures are observed for worksite operations worldwide. On the contrary, the operations at road intersections do not show the same degree of overlap for some commands and thus fail to support the hypothesis. However, it has become clear that all gestures have a base in affordance, and thus an affordance-based vehicle control (Moratz and Tenbrink, 2008; Murphy, 1999; Saffiotti and Broxvall, 2008) may be the key for interaction with self-driving vehicles. Affordance, in this case, is exuded by the visually perceivable functional aspects of the hand gestures, which must be shared by the self-driving vehicle.
This chapter presents a negotiation framework between pedestrians and self-driving vehicles describing the processing and exchange of negotiation cues among them, addressing the following research questions (Section 1.3).

1. What are the steps in self-driving vehicle-pedestrian negotiations?

2. Can self-driving vehicle successfully negotiate with pedestrians for their right of way at intersections with an understanding of physical constraints along with pedestrian’s intentions, in order to reduce their waiting times?

The research hypothesis is that the negotiation between self-driving vehicles and pedestrians will result in a better coordination among both parties, reduce the travel time of vehicles, and thus improve the overall traffic flow at these crossing points.

To prove the above hypothesis, this work first conceptualizes the vehicle-pedestrian negotiation process. Secondly, the conceptual model is realized through agent based simulation using SUMO and MATLAB. The simulation focuses on the interaction of a pedestrian with the leader vehicle (in a random vehicle flow) approaching the intersection. Particularly, it compares the proposed negotiation model to the conservative assumption that a self-driving vehicle always stops for a pedestrian with an intention to cross. The considered parameters are the traffic disturbance and pedestrian delay. The traffic
disturbance is measured in terms of the average travel time of vehicles, the time headway between vehicles, and the overall intersection throughput.

Different road scenarios may be complex due to the presence of multiple interacting agents. Before considering those complexities, as a first step in defining negotiation concepts on roads, this chapter only focuses on the simple case of negotiation between a single self-driving car and a single pedestrian. The simulation results show that the travel time of negotiating vehicles is significantly reduced, thus improving the overall traffic flow. This basic model demonstrates the positive impact of negotiation on traffic flow which motivates to do future research in more complex scenarios. This model can be extended to multi person-multi vehicle interaction which is the next step in this work.

4.2 NEGOTIATION FRAMEWORK

This section discusses the process of negotiation, and then describes a conceptual model for the vehicle-pedestrian negotiation.

4.2.1 What is negotiation?

In business literature, negotiation is defined as the ‘process of combining conflicting positions into a common position, under a decision rule of unanimity’ (Zartman, 1988). This means, negotiation parties have to agree upon a solution for a conflict. The agreement is advanced by their common interest, mutual perception and dependence (Tanya and Azeta, 2008). The theory of principled negotiation (seeking win-win solutions) defines seven prescriptive components for negotiation comprising interests, people, options, legitimacy, alternatives, commitments, and communication. As a starting point for defining a negotiation process in traffic, these elements of negotiation theory are explored below:

a. Identifying parties and their interests: The parties involved in the negotiation have underlying interests which can be identified from the parties’ hidden or stated objectives.

b. Identifying the options: The possible solutions to the problem shared by both parties should be explored during negotiation.

c. Criteria: Fair criteria for a joint decision-making should be established to reach an agreement among parties.

d. Commitments: Once an agreement is reached the parties should make commitments to honor it.

e. Alternatives: The alternative solutions must be available to meet one’s goals if there is no cooperation from the other side.
f. Communication: An effective communication is important to describe one’s intention to the other party and also to learn about the other party’s intentions during the negotiation process.

The above elements of the negotiation theory are used for defining the process of negotiation in traffic, which is discussed in the next section.

4.2.2 Conceptual model

The situation to be studied is depicted in Fig 1. The vehicle and the pedestrian are approaching an unmarked intersection and their goal is to pass the intersection with minimum waiting time. Each party estimates its time to reach the conflict point ($T_{veh}, T_{ped}$). In a conflicting situation, both parties will try to negotiate for the right of way and at least one of them has to change their intention to allow the other party to pass first.

![Figure 1: Vehicle-pedestrian interaction scenario: The interaction environment is restricted to unregulated junctions where the pedestrian appears at the curbside and is attempting to cross the road (screen-shot in SUMO).](image)

The conceptual model of a negotiation framework is presented in Fig. 2. At any time $t$, the two agents (vehicle and pedestrian) have a particular speed and direction of movement. It is assumed that both agents are able to communicate their intentions through a communication channel. For example, the vehicle can blow the horn, use light indicators, or send text messages to alert the pedestrian, and the pedestrian can use eye gaze and gestures to indicate their intentions. It is assumed that the vehicle is able to detect the gaze and gestures of pedestrian through appropriate sensors with a known accuracy of detection. This assumption is reasonable as technologies such as face and gesture recognition already exist in other domains (Section 2.4). So it can be expected that the future self-driving cars will also be able
to detect and decode cues from human road users (gaze, hand signals, and body movement).

Figure 2: The proposed vehicle-pedestrian negotiation framework.

The vehicle continuously looks for any pedestrian around, and whenever a pedestrian is detected near the curbside, it checks for any conflict with the estimated trajectory of the pedestrian. It perceives the speed, direction, and other cues of the pedestrian to estimate their intention to yield or not to yield. Similarly, the pedestrian also perceives speed, direction, and other cues of the vehicle. Each party estimates the intention of the other party as a function of these parameters\(^1\).

If there is a conflict in the intentions of two parties, then negotiation starts at that instance. The vehicle estimates its chance to pass first and communicates its intentions in the form of a communication act (for example, speeding up or slowing down, or using indicators to warn the pedestrian). The pedestrian also has an interest to pass first. Both parties form a negotiation strategy based on social rules and physical constraints. However, this work only focuses on physical constraints to formulate the negotiation strategy as social rules play a more significant role in presence of multiple vehicles and pedestrians, which is discussed in the extension of this work in Chapter 5.

Both parties are looking for an agreement during the negotiation process. The pedestrian is expected to react to the vehicle’s action. This reaction may be a change in their intentions. The pedestrian may

---

1 In the context of intention estimation, algorithms have already been developed in the existing literature to detect the possible actions of pedestrians and drivers (Molchanov et al., 2015; Rasouli, Kotseruba, and Tsotsos, 2017)
honor the vehicle’s intention to pass first and stop at the curbside (or wave allowing the vehicle to pass first). In this case an agreement between two parties is established.

In another case, the pedestrian may show an aggressive behavior and continue to cross (speeding up action). The vehicle will either decide to stop (slow down) in the next step or continue to negotiate its chance to pass first based on its assessment of the physical constraints. In this negotiation process, non-verbal cues are exchanged continuously till an agreement is reached (in which case the negotiation ends).

The negotiation model benefits the vehicle if it encounters a cooperative pedestrian, but this model also ensures that the vehicle exhibits conservative behavior towards an aggressive pedestrian to maintain safety on the road. In case of large uncertainty in the pedestrians’ intention to yield, the vehicle always slows down for a pedestrian to cross. Note that in the actual scenarios, self-driving vehicles will use machine learning methods to learn pedestrian’s intentions based on their gestures and other behavior. This sensing and data analytical process by the vehicle is out of the scope of this work. Instead, we start with a certainty estimate. A certain agreement or disagreement in this work means that the vehicle is nearly able to predict the pedestrian’s intentions, for example, it can clearly distinguish between a moving and a stopped pedestrian - this assumption is based on existing literature and promising advancement in the machine learning technologies with applications to automated driving (which is already reviewed in Chapter 2). Thus, safety is the overarching principle, but in contrast to a standard conservative behavior the one-to-one negotiation is also providing gains in throughput.

4.2.3 Vehicle-pedestrian interaction scenarios

The different scenarios of everyday negotiation between vehicles\(^2\) and pedestrians are discussed below. Note that in these examples the communication is through non-verbal cues and the parties can perceive each other’s intentions through their actions (such as indicating one’s intention of not to yield by speeding up or gesturing to stop).

In the first three scenarios, the vehicle indicates its desire to pass first as its estimated time to cross is less than that of the pedestrian ($T_{veh} < T_{ped}$, Fig. 1). This message is communicated to the pedestrian through some communication channel.

**Scenario 1**: The pedestrian shows an aggressive behavior and decides to cross first (reacts by starting to cross). The vehicle perceives this intention of the pedestrian and prepares to slow down.

**Scenario 2**: The pedestrian honors the social rules and agrees to yield to the vehicle. The pedestrian slows down (acknowledgement

\(^2\) In current traffic the interaction is with drivers of vehicles
in negotiation) which is perceived by the vehicle as an agreement, and in the next step the vehicle speeds up to pass the intersection.

Scenario 3: Another case is when the vehicle can’t stop before the crossing point due to acceleration constraints, and thus generates an alert to the pedestrian. In this scenario, the vehicle indicates to pass first but the pedestrian shows an aggressive behavior by starting to cross anyway. In the next step, the vehicle generates an alert and the pedestrian reacts by stopping for the vehicle.

Scenario 4: The pedestrian initiated the negotiation by indicating to pass first (through gestures). The vehicle perceives this intention and prepares to slow down for the vehicle. The slowing down action of the vehicle is assumed as an agreement by the pedestrian. The pedestrian crosses first.

4.2.4 Negotiation strategy

The negotiation strategy is based on pedestrian’s behavior, which may be either aggressive or cooperative. In this work the focus is to formulate negotiation strategies for the vehicle to deal with these two types of pedestrian behavior which have some indirect benefits to pedestrian as well. This section describes the formulation of advisory speed for vehicle.

The negotiation starts when a vehicle detects a pedestrian approaching the curbside. First, the vehicle estimates the intention of the pedestrian in terms of chances of them yielding (Y) or not yielding (NY) to the vehicle.

Secondly, the vehicle forecasts the speed limits within which it can move in the current situation:

a. Lower Speed Bound (LSB): The required speed of the vehicle such that the pedestrian crosses the end of the intersection before the vehicle reaches the starting edge of intersection.

b. Upper Speed Bound (USB): This is the required maximum speed to pass the intersection before the pedestrian steps on the starting edge of the intersection.

To initiate the negotiation, next the vehicle offers to pass first, if (i) it can pass before the pedestrian based on its knowledge of current motion parameters of both parties, (ii) or it cannot stop before the pedestrian finishes crossing (alert generated). If the pedestrian expresses an intention to pass first then the vehicle estimates its chances of negotiation based on the conditions described above.

Advisory speed for vehicle: The advisory speed for the vehicle is based on the vehicle understanding of pedestrian’s intentions at any instance. If the chance of the pedestrian yielding is high then the vehicle speeds up (within limits) to pass first and reduce the waiting time for the pedestrian as a reward, rather than moving with the same speed
towards the crossing point. On the other hand, if the chance of yielding is low, then the vehicle should slow down and negotiate again its chance to pass first. Human drivers do this intuitively and adjust their speed considering the confusion in estimating what a pedestrian is going to do next. The uncertainty involved in estimating pedestrian’s intention should be considered to calculate advisory speed of vehicle. Thus, the advisory speed can be computed by taking the weighted average of predicted lower and upper speed bounds ($LSB$ and $USB$).

$$\text{advisory speed} = Y \times USB + NY \times LSB$$

Here, weights are taken as the perceived pedestrian’s chances of yielding or not yielding ($Y$ and $NY$), where $Y > NY$ for a yielding pedestrian.

The stepwise algorithm for negotiation process by the vehicle is presented in Algorithm 1. The advisory speed for vehicle is computed at the end of each negotiation cycle. The associated terminology is listed in Table 3.

Table 3: Terminology

<table>
<thead>
<tr>
<th>Term</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d_{veh}$</td>
<td>distance of vehicle from the starting edge of intersection</td>
</tr>
<tr>
<td>$d_{ped}$</td>
<td>distance of pedestrian from the starting edge of intersection</td>
</tr>
<tr>
<td>$v_{veh}$</td>
<td>current speed of vehicle</td>
</tr>
<tr>
<td>$v_{ped}$</td>
<td>current speed of pedestrian</td>
</tr>
<tr>
<td>$TTR_{ped}$</td>
<td>time taken by pedestrian to reach starting edge of intersection</td>
</tr>
<tr>
<td>$TTR_{veh}$</td>
<td>time taken by vehicle to reach starting edge of intersection</td>
</tr>
<tr>
<td>$w$</td>
<td>width of the lane</td>
</tr>
<tr>
<td>$l$</td>
<td>length of the vehicle</td>
</tr>
<tr>
<td>MAXIMUM</td>
<td>maximum allowed speed for vehicles</td>
</tr>
<tr>
<td>accelToStop</td>
<td>required deceleration to stop before intersection</td>
</tr>
<tr>
<td>accelLimit</td>
<td>acceleration or deceleration limit of the vehicle</td>
</tr>
<tr>
<td>ALERT</td>
<td>status variable to alert pedestrian</td>
</tr>
<tr>
<td>gaze</td>
<td>accuracy of pedestrian’s gaze detection by the vehicle</td>
</tr>
<tr>
<td>gesture</td>
<td>accuracy of pedestrian’s gesture detection by the vehicle</td>
</tr>
</tbody>
</table>
Algorithm 1 Pseudo-algorithm for negotiation by vehicle

Input: Motion and indicator parameters of agents  
Output: Advisory speed for vehicle

1: check if pedestrian has reached 2 m before the curbside  
2: for each negotiation cycle do  
3: if no trajectory conflict with the pedestrian then  
4: no negotiation required; CONTINUE  
5: else  
6: estimate intentions of the pedestrian  
7: \[ Y = \text{IntentionEstimator}(\text{gaze}, \text{gesture}, \nu_{\text{ped}}) \]  
8: \[ NY = 1 - Y; \]  
9: if acknowledgement to yield by the pedestrian with some action (Y >> NY) then  
10: (agreement is reached in favour of vehicle);  
11: else if ALERT is true then  
12: vehicle generates an alert to the pedestrian  
13: else  
14: (conflict in intentions)  
15: if \( T_{\text{veh}} < T_{\text{ped}} \) then  
16: vehicle indicates to pass first  
17: else  
18: (vehicle waits for pedestrian’s action)  
19: end if  
20: end if  
21: compute minimum required speed (LSB)  
22: \[ T_{\text{TR ped}} := (d_{\text{ped}} + w)/\nu_{\text{ped}} \]  
23: LSB := \( d_{\text{veh}}/T_{\text{TR ped}} \)  
24: compute maximum required speed (USB)  
25: \[ USB := (d_{\text{veh}} + w + l)/T_{\text{TR ped}} \]  
26: USB := \( \min(USB, \text{MAXIMUM}) \)  
27: compute the advisory speed  
28: \( \text{advisory speed} := Y \times USB + NY \times LSB \)  
29: check whether advisory speed satisfies acceleration limits  
30: update advisory speed keeping the acceleration limits  
31: compute required deceleration to stop before start of intersection (accelToStop)  
32: compute ALERT status:  
33: if accelToStop > accelLimit OR \( d_{\text{veh}} < 0 \) then  
34: ALERT := true  
35: advisory speed = USB  
36: else  
37: ALERT := false  
38: end if  
39: end if  
40: return advisory speed  
41: end for
4.3 EXPERIMENT DESIGN

The above model is tested in a simulation environment. This section explains the details of the experiments involved.

4.3.1 Simulation environment

The simulation of vehicle-pedestrian interaction scenario is done using MATLAB and SUMO (Simulation of Urban Mobility). The TraCI (Traffic Control Interface) protocol is used to interact with SUMO in a client-server scenario. A random vehicle flow of 800 vehicles/hour is generated in SUMO3, and the simulation is run for about 7 hours (24000 steps of 1s). The flow of vehicles generated by SUMO is by default binomially distributed which approximates a Poisson distribution. This simulation is run for two different frequencies of pedestrian flow – every 35s (total 685 pedestrians) in the first experiment, and every 14s (total 1714 pedestrians) in another experiment. The pedestrian frequency was set low to avoid the cases of vehicle’s interaction with multiple pedestrians at intersection which is not the concern of this chapter. The pedestrian behavior modeling is described in Section 4.3.3.

4.3.2 Negotiation model

In the proposed negotiation model, the interaction with a pedestrian starts when the pedestrian reaches a distance of 2m or less from the curbside4. From this instance, the negotiation model algorithm is applied. At the time of their appearance, their distance from the lead vehicle is different each time. In the free flow of vehicle, each vehicle starts (enters the simulation) with zero speed and accelerates (upto maximum allowable speed). Most of the vehicles have accelerated to the maximum speed at a distance of around 40m from the conflict point. Thus, the speed of leader vehicle at the time of pedestrian encounter depends on its distance from the conflict point. For each step in the simulation, parameters recorded are speed and position of vehicle and pedestrian, and their respective distance from the crossing point (both at lane center and at curbside). The assumptions in this modeling are:

i) The environment considered is an unregulated road intersection and the vehicles are moving along a straight line on the road; there is no lane changing or passing around the pedestrian.

3 This value is considered to be a medium traffic flow in SUMO, maximum flow representing peak hour traffic allowed in SUMO is 1200 vehicles/hour.
4 An arbitrary threshold is assumed here; in real life settings this value depends on the pedestrian detection range of the vehicle.
ii) Vehicles enter and exit the simulation in the same order; there is no overtaking.

iii) Different road scenarios may be complex due to the presence of multiple interacting agents. Before considering those complexities, as a first step in defining negotiation concepts on roads, this work only focuses on the simple case of negotiation between a single self-driving car and a single pedestrian.

iv) The approaching pedestrian interacts only with the next approaching vehicle.

v) The current model considers only a vehicle’s interaction with a pedestrian approaching from a conflicting direction whose goal is to cross the intersection; other road users as well as other pedestrian behaviors are not considered.

Assumptions (i-iv) allow a proof of concept for the negotiation model. Assumption (v) suggests that the negotiation model has to be embedded in a multi-agent framework in future.

4.3.3 Pedestrian behavior modeling

Pedestrians are modeled with a dynamic behavior in the simulations. In the first experiment, a pedestrian is introduced into the environment every 35 s from a fixed origin (at some distance from the crossing point). In a second experiment the pedestrian frequency is changed to 14 s. By default, the pedestrian is moving with an average walking speed (assuming 1.2 m/s). The pedestrian stops if (i) the oncoming vehicle is at less than a distance of 30 m from the intersection, or (ii) an alert is generated by the vehicle because it cannot stop before the pedestrian crosses due to its deceleration constraints.

Apart from the motion dynamics, there is an intention value associated with pedestrian behavior at any simulation step. Here, the intention value means: the pedestrian’s chances of yielding \( Y \) or not yielding \( NY = 1 - Y \) as perceived by the vehicle. Since gaze and gestures of pedestrians cannot be modeled in SUMO, and neither can the perception of these by vehicles, the initial intention values are assigned randomly to show cooperative \( Y > NY \) or aggressive behavior \( NY > Y \). This value changes depending on the distance of the vehicle. The waiting time is minimum for the vehicles if pedestrian always shows a cooperative behavior towards them. The waiting time is maximum for the vehicles if they always encounter an aggressive pedestrian in which case the negotiation and conservative model would produce same results. The assumption here of 50% likelihood of encountering an aggressive or cooperative pedestrian demonstrates the average between the two extremes. The model can be adjusted for local culture.
Initially, the pedestrian is approaching the intersection to pass first with an average walking speed so the intention value is assigned as \( Y = 0.2 \). But during negotiation, if the pedestrian slows down or stops for the vehicle to pass first then the intention value changes (value of \( Y \) changes proportionally to the change in speed of pedestrian). The possible interaction scenarios in the simulation have been discussed in Section 4.2.3.

4.3.4 Conservative vehicle model

A second simulation with a conservative vehicle behavior provides the benchmark for comparing the performance of the proposed negotiation model. A vehicle shows conservative behavior if it always stops when it detects a pedestrian within 2m of the curbside, i.e., with the intention to cross. The arbitrary threshold of 2m is an assumption in the simulation, where pedestrians only move in order to cross the street; it is not intended to state that real-world vehicles apply this threshold. In the real world, vehicles have to use machine learning methods to detect pedestrians and to detect their intentions, for example, from trajectory extrapolation (Bai et al., 2015; Bandyopadhyay et al., 2013; Long, Liu, and Pan, 2017). In this case the vehicle waits until the pedestrian finishes crossing. This mimics the current state of self-driving vehicles. The pedestrian behavior, in this case, is modeled to show an aggressive behavior and always gets the right of way (passes first). The simulation environment is the same as the negotiation model.

4.3.5 Observables

For each model, the following parameters are observed at the time of simulation to measure the traffic disturbance:

a. Travel time of vehicles: This is the time vehicle takes to pass the intersection from the starting point. The timestamps at which a vehicle enters the simulation environment (entry) and passes the other end of the intersection (exit) are recorded for each vehicle in the simulation. The entry and exit timestamps provide the travel time for each vehicle.

b. Time headway: This is the difference in passing time of successive vehicles in the traffic flow. The time headway for each vehicle pair is calculated by taking the exit timestamps difference of the current and last vehicle which passed the intersection.

c. Pedestrian delay: This is measured in terms of the time taken by the pedestrians to cross the road (from curbside to curbside). This includes the waiting time for a pedestrian at the curbside.
d. **Overall intersection throughput**: Throughput is the number of vehicles passing the crossing point per hour. The overall crossing point throughput is calculated as the total number of vehicles which passed the crossing point divided by the simulation run time.

### 4.4 RESULTS AND DISCUSSION

The performance of the proposed model is measured in terms of travel time analysis of vehicles, time-headway analysis, and the overall intersection throughput analysis. This section provides the results and related discussions for each of the analysis.

#### 4.4.1 Travel time analysis

The travel time series for the first 30 vehicles is shown in Fig. 3. It is clear from the graph that the travel time of vehicles is less for negotiating vehicles (in blue color) as compared to the conservative vehicles (in red color). The peak indicates the increase in travel time of vehicles due to waiting for pedestrian to cross. This waiting time is higher for leader vehicles interacting with the pedestrian.

#### 4.4.1.1 Pedestrian frequency 35s

The first three data points in the conservative model (Fig. 3a, red) show that the leader vehicle interacting with a pedestrian is delayed with maximum waiting time. This delay is propagated to the vehicles queuing up behind. After a few of delayed vehicles have passed, the vehicle flow stabilizes again (represented in red data points 4-8) until another pedestrian is encountered. On the other hand, this situation is improved in the negotiation model (blue color) as negotiating vehicles can anticipate the situation and slow down or speed up in agreement with the pedestrian. The results show that the first vehicle is able to negotiate and pass first with minimum total travel time. The second vehicle slows down for the pedestrian and experiences some delay but the following vehicles are not affected. The negotiating vehicle travel pattern shows that vehicles in queue are less affected as compared to the conservative model.

#### 4.4.1.2 Pedestrian frequency 14s

If the pedestrian frequency is increased to 14s, then the travel time for vehicles further increases (Fig. 3b). The first three vehicles in both models pass without conflicting with a pedestrian. The fourth conservative vehicle (red) stops for the pedestrian and experiences some delay, which is propagated to the following vehicles. Due to frequent encounters with pedestrians more vehicles are experiencing delays,
Figure 3: Travel time series: Travel time of first 30 vehicles in the simulation for negotiation model (blue) and conservative model (red).

(a) Pedestrian frequency = 35s

(b) Pedestrian frequency = 14s
which indicates that traffic density increases over time, thus causing disturbance in traffic flow and congestion on roads. This is evident from the simulation results as the average travel time for the first 100 vehicles is 16.2 s, which increases to 43.5 s for around 5000 vehicles at the end of simulation. This high increase in average travel time of conservative vehicles reveals the accumulation of delays over time affecting the flow of vehicles near the points of crossing. In case of the negotiation model (blue), the travel time of vehicles is higher than in the previous experiment due to the higher pedestrian frequency. But the lower peaks in the negotiation model still show less traffic disturbance as compared to the conservative model. This is also evident from the average travel time for negotiating vehicles, which remains almost constant at the end of the simulation (average travel time 11.8 s).

4.4.2 Time headway analysis

The traffic disturbance can also be understood in terms of the time headway distribution for vehicles in both models, which is represented in Fig. 4 and Fig. 5. In road traffic, a minimum time headway of two seconds to the vehicle in front is to be maintained to avoid any rear-end collisions and the same is implemented in SUMO by default. In simulations, the average headway of vehicles in the initial vehicular flow is 5 s. The quantitative distribution of time headway of vehicles (numbers represent the % of total vehicles) for both models is listed in Table 4 and Table 5, respectively. This will be further discussed in the following sections.

4.4.2.1 Pedestrian frequency 35 s

Interestingly, the average time headway for both models is the same (about 4.5 s) but the variance in the distribution of the conservative model is higher. An analysis of variance using F-Test showed that this difference is significant ($F_{1,5330} = 2.97, p < 0.05$). This indicates that traffic disturbance is higher in conservative model. The graphical representation of the time headway distribution for the conservative model is presented in Fig. 4b.

<table>
<thead>
<tr>
<th>TH</th>
<th>2s</th>
<th>4s</th>
<th>6s</th>
<th>8s</th>
<th>10s</th>
<th>12s</th>
<th>14s</th>
</tr>
</thead>
<tbody>
<tr>
<td>NM (%)</td>
<td>10.9</td>
<td>42.7</td>
<td>35.6</td>
<td>9.0</td>
<td>1.7</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>CM (%)</td>
<td>27.0</td>
<td>36.3</td>
<td>23.6</td>
<td>0.7</td>
<td>4.6</td>
<td>6.4</td>
<td>1.4</td>
</tr>
</tbody>
</table>

In Fig. 4b, the higher time headway values (10s, 12s, and 14s) reflect the higher waiting time for leader vehicles. These leader vehicles
Figure 4: Time headway analysis with the pedestrian frequency of 35s.
interact with the pedestrians and count for 12.3% of the total vehicles in the flow. Table 4 shows that the stopping of leader vehicles has delayed another 27% of the total vehicles as they have the minimum time headway (2s). This implies that the flow of conservative vehicles is not uniform and vehicles are stacking up (waiting behind leader) during pedestrian encounters, causing disturbance or congestion. However, in the negotiation model (Fig. 4a) the maximum headway is 10s, and 80% of the total vehicles have a time headway between 4s to 6s representing a smoother flow of vehicles (Table 4). Negotiation improves the flow of 20% of those vehicles that were affected by delay in the conservative model, thus reducing the disturbance in traffic.

4.4.2.2 Pedestrian frequency 14s

It is expected that increasing the pedestrian frequency will increase the waiting time for vehicles. The results show that negotiation performs better in this case as well. The graphical representation shows that the time headway distribution is uniform for negotiations (Fig. 5a) as compared to the conservative model, which still shows a large variance in the distribution (Fig. 5b). In this case also, the analysis of variance using F-Test showed that this difference is significant ($F_{1,5127,5330} = 2.05, p < 0.05$).

Table 5: Time headway (TH) distribution for negotiation (NM) and conservative (CM) model (pedestrian frequency 14s)

<table>
<thead>
<tr>
<th>TH</th>
<th>2s</th>
<th>4s</th>
<th>6s</th>
<th>8s</th>
<th>10s</th>
<th>12s</th>
<th>14s</th>
</tr>
</thead>
<tbody>
<tr>
<td>NM (%)</td>
<td>26.3</td>
<td>34.6</td>
<td>13.2</td>
<td>19.4</td>
<td>6.5</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>CM (%)</td>
<td>49.1</td>
<td>17.8</td>
<td>0.0</td>
<td>3.2</td>
<td>29.6</td>
<td>0.1</td>
<td>0.0</td>
</tr>
</tbody>
</table>

In the conservative model, the number of leader vehicles stopping for pedestrians increases by 30% when the pedestrian frequency is increased to 14s (Table 5). Also, the number of following vehicles delayed due to frequent pedestrian encounters is about 50% (headway of 2s) in this case. But with negotiation, about 50% of the total vehicles passed with time headway between 4s to 6s, while only 26% of the total vehicles are affected by slowing down of the lead vehicles. The results show that negotiation has improved the traffic flow as compared to the conservative vehicles in line of the arguments stated in previous sections. Both travel time and time headway analysis results support the hypothesis of this research.

4.4.3 Throughput analysis

Throughput is measured as described in Section 4.3.5. The following section discusses throughput analysis for both experiment cases.
Figure 5: Time headway analysis with the pedestrian frequency of 14s.
4.4.3.1 Pedestrian frequency 35s

The results of experiments with pedestrian frequency of 35s reveal an interesting fact: Although travel time of vehicles show significant differences in the two models, overall throughput at crossing points does not change. This observation can be explained by the analysis of crossing point exit timestamps of vehicles in the two models (Fig. 6a). The peaks in the time series show the interruption in free flow of traffic by the pedestrians. These peaks are higher for conservative vehicles (red color). The dots in the curve around these peaks represent the waiting vehicles.

![Exit time analysis: The exit timestamp of vehicles in SUMO is plotted against the simulation runtime. The above plot is shown for first 30 vehicles to visualize the pattern in traffic flow.](image-url)
The above results show that negotiation brings down these peaks by reducing the waiting time of vehicles (blue color). The difference in exit timestamps for the same vehicles in both models is higher for the first few waiting vehicles. Then the delay in waiting of the conservative vehicles reduces, and after some time conservative model converges to the negotiation model (Fig. 6a). The delayed vehicles are queued up behind a leader vehicle while they are waiting for a pedestrian to cross. As the pedestrian passes, the stacked vehicles accelerate to pass one after the other without any interruption. The time headway in this case is minimum (2s), which is reflected in the headway distribution (Table 4). After the delayed vehicles are cleared up from the road near the crossing point, the traffic density stabilizes again until the next pedestrian is encountered.

Thus, overall throughput does not change at the end of simulation. However, if throughput is computed at a time when a queue of vehicles is waiting at the crossing point, then the throughput difference in the two models will be significant. This leads to another hypothesis that if pedestrian frequency is increased then there should be significant difference in intersection throughput, i.e., negotiation model should perform better than conservative model. This is discussed next by changing the pedestrian frequency to every 14s.

4.4.3.2 Pedestrian frequency 14s

By increasing the pedestrian frequency the distance between exit timestamps of both models increases as well (Fig. 6b). The above hypothesis is supported by the throughput analysis results in Fig. 7. The graph shows the total number of vehicles that passed the intersection in the simulation. The results show that by negotiation around 200 more vehicles passed in total as compared to the conservative model. This observation also supports the observations in Sections 4.4.1 and 4.4.2 that traffic flow is improved by negotiation as more vehicles are passing through the intersection.
Figure 7: Throughput analysis: The graph shows the exit timestamp of each vehicle at intersection until the end of simulation (24000s). The two time series represent the negotiation (blue) and conservative (red) model.

4.5 Conclusions

This chapter presents a conceptual model for negotiation between self-driving vehicles and pedestrians which is realized through agent based simulation in SUMO and MATLAB. The proposed model is compared to the conservative behavior of self-driving vehicles of always stopping for the pedestrians stepping into the road to cross. This model suggests a negotiation framework for vehicles to negotiate with pedestrians based on physical constraints given that a vehicle is certain of the pedestrian’s intentions. This research answers the related research questions in this chapter. The simulation results show that the average travel time for negotiating vehicles is improved and the traffic disturbance is reduced as compared to the conservative vehicles. These results support the hypothesis of this research.

Another interesting observation from this model is that although the travel time of vehicles is improved, there is no difference in the overall intersection throughput in the two models when pedestrian frequency is low. However, this difference in throughput increases when the pedestrian frequency is increased in a different experiment – negotiation model performs better and allows more vehicles to pass the intersection. This indicates that current conservative behavior of self-driving cars will cause congestion on roads and negotiation is a solution to this problem.

The negotiation process has some costs and benefits to both parties. The waiting time for vehicles at intersections is reduced but pedestrians may experience some delay in crossing. However, this pedestrian
delay is much less than the waiting time for conservative vehicles. This means, negotiation will benefit multiple vehicles by reducing their waiting times, and allow them to maintain a smooth speed profile and reduce congestion on roads. On the other hand, at the cost of some delay (which is less than waiting time for vehicles) pedestrians have better coordination with the driverless vehicles. The other indirect benefits to them are reduced emission hazards and congestion-free surroundings providing them a liveable community.

The proposed model only considers the simple cases of negotiation between one vehicle and one pedestrian. Also, the negotiation strategies are based on physical constraints. But in a more realistic scenario negotiation strategies of both parties are affected by the presence of multiple vehicles and pedestrians around the interaction site. While the presented single vehicle and single pedestrian negotiation model is based on one-to-one interactions, the negotiation among multiple vehicles and multiple pedestrians relies to a larger degree on informal social rules including groups. Thus, in the next chapter the above model will be encapsulated in an expanded model that will deal with multiple vehicles and multiple pedestrians by incorporating social rules of groups in the negotiation criteria. Formulating such informal social rules will be challenging as they also depend on the behavior of pedestrians. The focus of the next experiments will be to identify and formulate negotiation strategies in complex scenarios which should mimic the everyday negotiation on roads.
This chapter is based on the article “Social rules for negotiating the right of way among self-driving vehicles and pedestrians” submitted to a journal for review by Gupta, Vasardani, Lohani, and Winter (2019). As such, most of the content in this chapter is compiled from this publication. My contribution as a first author in this work includes proposing the research problem and hypothesis; developing the model and rules; designing experiments and performing the analysis; evaluating the hypothesis; and also providing related discussions and conclusions. The entire work was supervised by my supervisor Prof Stephan Winter, and co-supervisor Dr Maria Vasardani, and external supervisor Prof Bharat Lohani, who actively provided their suggestions and feedback at each stage of this research.

5.1 Introduction

The following research questions from Section 1.3 are investigated in this chapter:

1. Which informal social rules exist among human drivers and pedestrians affecting their crossing decisions?

2. In addition to physical constraints, can social rules increase the chances for self-driving vehicles’ successful negotiations with pedestrians for their right of way?

This chapter focuses on self-driving vehicles’ negotiations with pedestrians based on informal social rules. This negotiation process assumes an estimation of the pedestrians’ intentions (Chapter 4), and goes further by implementing informal and fuzzy social rules for interaction. The latter is novel for a self-driving vehicle, enabling it to take human-like decisions to resolve conflict situations. The rules will be embedded in a negotiation process for an agreement with the pedestrians about who is getting the right of way, without ever compromising safety. The proposed vehicle-pedestrian negotiation model is suited for multiple vehicles on the road and multiple pedestrians queuing up. The hypothesis of this research is that the introduction of social rules in the negotiation between self-driving vehicles and pedestrians will reduce the waiting times for vehicles and increase the intersection throughput.

To examine this hypothesis, the social rules of negotiations are conceptualized, and the negotiation model introduced in the previous chapter is expanded to include those social rules. In order to test
the hypothesis in a controlled environment, this conceptual model is also implemented in a simulation similar to the experiments in previous chapter. The vehicle-pedestrian interaction environment is an unmarked intersection. Compared are the accumulated waiting time of the vehicles, the average number of vehicles in the waiting queue, and the overall throughput at crossing points. Six different conditions of traffic are considered by varying the frequency of vehicles and pedestrians, and the overall impact of negotiation is discussed in each case.

To our knowledge, a negotiation model introducing social rules for decision making in traffic is novel. This work demonstrates how negotiation reduces the conflict of interests between groups of vehicles and pedestrians in typical traffic conditions and balances the right of way among them. The simulation results show that the negotiations reduce the waiting times and waiting queues of vehicles compared to the conservative vehicle behavior. The reduction of waiting times for the vehicles is coming at the cost of pedestrians, but the simulation shows also that these waiting times for pedestrians do not exceed those at signalized intersections.

5.2 Extended negotiation framework

The following negotiation model aims for agreement among a party of (potentially multiple) vehicles and a party of (potentially multiple) pedestrians on who will pass first at an unregulated intersection. An example is presented in Fig. 8.

Figure 8: Interaction at an unregulated junction where the vehicles moving in a flexible and variable queue are negotiating for the right of way with pedestrians waiting at the curbside to cross the road.

5.2.1 Elements of the negotiation model

The following terms and assumptions are required:

1. Vehicle queue: A vehicle queue is defined by at least a lead vehicle. Further vehicles qualify to be in a queue of the lead vehicle
if they are maintaining a time headway of about 2s (Ayres et al., 2001). In floating traffic, vehicles may join or leave a moving queue at any time.

2. Pedestrian group: A pedestrian group is an informal formation of at least one lead pedestrian and (potentially) multiple pedestrians following this lead person. A pedestrian qualifies to be in the group of the lead pedestrian if they are within an arbitrary fix threshold of any pedestrian already in the pedestrian group. In the movement dynamics on sidewalks, pedestrians may join or leave a group at any time.

3. Vehicle safe distance: This is the distance required so that a vehicle can stop before the intersection with given deceleration constraints. If a vehicle reaches the safe distance and no agreement has been made, the vehicle will brake but may continue to communicate and negotiate.

4. Gap: A gap in the vehicle or pedestrian flow occurs between consecutive vehicle queues, or between consecutive pedestrian groups respectively.

5. Pedestrian's maximum waiting time: This is the maximum time a pedestrian is willing to wait at the intersection.

6. Alert: A vehicle generates an alert when the required deceleration to stop before the intersection is greater than the physically possible deceleration, in which case the vehicle cannot stop before the pedestrian crosses.

The lead vehicle perceives pedestrian groups arriving near the intersection. The first person from the intersection is perceived as the group leader. Similarly, pedestrians assume the first vehicle in a vehicle queue as the lead vehicle. The lead vehicle also has knowledge about the positions and speeds of vehicles following it through vehicle-to-vehicle communication. The negotiation is led by the two leaders representing the two parties.

Each follower pedestrian in the pedestrian group follows the social norms and cooperates with the lead pedestrian’s decision (following a group behavior). This means, if the lead pedestrian has decided to stop (yield to the vehicle), then the following pedestrians in the group also stop. However, while they resume walking after waiting and when the lead pedestrian has stepped out of the curbside, the next pedestrian in the group becomes the lead pedestrian. The current lead pedestrian interacts with the lead vehicle and decides whether to follow the previous lead pedestrian, or to allow the vehicle to pass first (keeping in mind the social rules and physical constraints). Similarly, each following vehicle in the vehicle queue follows the decision
of the lead vehicle. Once the lead vehicle passes through the intersection, the next vehicle in the queue (which becomes the lead vehicle now) interacts with the lead pedestrian and negotiates its chance to pass first.

5.2.2 Conceptual negotiation model

The conceptual model for the negotiation framework is extended from the previous chapter and shown in Fig. 9. The first step, i.e. communication, is similar to the previous model except the group size parameter which is also included in the extended model. It is assumed that sensors in the vehicles detect and process movement and gestures of pedestrians or any changes in the environment, along with the number of pedestrians in their group. The model of negotiations between the two leaders representing the two parties is characterized by the following elements.

Figure 9: The proposed vehicle-pedestrian negotiation framework.

**Trajectory conflict:** The leaders of the parties approaching the intersection first check whether there is any potential conflict in their respective trajectories. If this is the case then as a next step, the leaders are interested in knowing the intentions of the opposite party.

**Intention estimation:** The two leaders perceive the location, speed and direction of movement of the members of the other party, and additionally the signals from the leader of the other party. The intention of the opposite party — yield ($Y$) or not-yield ($NY = 1 - Y$) — is estimated as a function of these parameters.
Matching intentions: If there is a conflict of the intentions, i.e., both parties have either the intention to pass first or to yield, then negotiation starts in order to match the intentions. If there is no conflict, no negotiation is required.

Negotiation criteria: Both party leaders form a negotiation strategy based on physical constraints and social rules. They estimate their chances to pass first and communicate their intentions. In the following iteration, both party leaders, now aware of the intentions of the respective other party leader, reconsider their own intentions. There may be a concession by one party, which when communicated leads to an agreement between the parties. But there may be also a refusal to concede (two aggressive negotiators still within safety constraints), or it could be a case of hesitation from both parties (two modest negotiators), in which case negotiation continues.

The iterative negotiation process concludes when either an agreement has been reached with one party committing to yield and the other party to pass first, or when safety constraints require the vehicle to concede anyway. Also, if matching intentions seem to have been emerged but the lead vehicle is not certain about the intentions of the pedestrians, it is also falling back to its safety-first principle (Luetge, 2017). In contrast to a standard conservative behavior, the negotiation is providing self-driving vehicles a fair chance of crossing first.

Advisory speed for vehicle: Similar to the previous model, the lead vehicle adjusts its speed at the end of each negotiation iteration to an advisory speed based on the estimated intentions of the pedestrians to yield, i.e., to the certainty of knowledge $Y$. The computed speed is also adjusted to acceleration constraints. The detailed algorithm for this speed adjustment has been discussed in the previous chapter (Chapter 4).

5.2.3 Social rules formulation

The following set of social rules are formulated for the negotiation process. They are derived from cases, or contexts, but should apply generically.

Case 1: Multiple pedestrians are arriving, and one vehicle is approaching towards the intersection.

R1: The vehicle sends an alert if it cannot stop before the pedestrians can finish crossing.

R2: The vehicle indicates to pass first (including a willingness to speed up within legal limits), if a pedestrian group is arriving.

R3: The lead pedestrian indicates to cross first, if the distance of the lead vehicle from the point of intersection is greater than, or equal to the vehicle safe distance, or if they have waited beyond their waiting time limit.
**R4:** In case the lead pedestrian has not provided any acknowledgment, the vehicle slows down.

Rule **R2** minimizes the waiting time for the vehicle, while **R3** ensures that pedestrians do not have to wait beyond their maximum waiting time. Rules **R1**, **R3** and **R4** ensure safety in this process. **R1** and **R3** account for physical constraints while **R4** keeps check on the condition of uncertainty about the lead pedestrian’s intention to agree during the negotiation.

*Case 2: A single pedestrian is arriving and a vehicle queue is approaching towards the intersection.*

**R5:** The lead vehicle indicates to pass first if there are more than two vehicles in its queue.

In this case, Rule **R5** gives the opportunity to release a number of vehicles at the intersection, as waiting for a single pedestrian causes a longer waiting time for multiple vehicles. Rule **R3** allows the pedestrian to cross when there is a safe gap from the lead vehicle.

*Case 3: The pedestrian count increases while waiting, and a vehicle queue is approaching.*

**R6:** The lead pedestrian indicates to cross when identifying a gap between queues of vehicles, or when the pedestrian group’s waiting time has reached its maximum.

If the number of waiting pedestrians increases with time while the vehicles are passing first, Rule **R6** balances the traffic flow by allowing the pedestrian group to cross when either there is a safe gap in the vehicle flow, or the lead pedestrian starts negotiation when their group waiting time has exceeded its maximum limit. In the latter case, the lead pedestrian indicates to cross.

*Case 4: The vehicle queue waiting at the intersection is increasing in length while a pedestrian group is crossing.*

**R7:** The lead vehicle indicates to pass if it has identified a gap between the groups of pedestrians, or the number of waiting vehicles in the queue is more than three.

**R8:** The current lead pedestrian indicates to pass if their waiting time has exceeded the maximum waiting time limit (while waiting for the previous pedestrians in the group to cross) and is also willing to cross.

The above rules, in this case, balance the waiting time for vehicles and pedestrians in denser traffic. Rule **R7** allows the waiting vehicle(s) to negotiate by finding a gap between groups of pedestrians at the point where the current lead pedestrian has not yet started crossing. While in the case of a lead pedestrian, Rules **R8** and **R3** allow them to move with the group if they have waited for too long. The workflow of vehicle-pedestrian negotiation incorporating these social rules is described in the next section.
This section formulates negotiation strategies for vehicles and pedestrians based on the above social rules. The strategies aim to balance chances of crossing first to both parties every so often, preventing them from waiting for too long.

If a single vehicle approaching the intersection encounters a group of pedestrians intending to cross (Case 1), then the vehicle initiates the negotiation (Rules $R_1$ and $R_2$). If the lead pedestrian yields to the vehicle, the vehicle continues to pass. If the lead pedestrian is willing to negotiate for the right of way on behalf of their group (Rule $R_3$), then negotiation continues. If pedestrians start crossing without any acknowledgment, then the vehicle applies Rule $R_4$, or sends an alert to stop pedestrians if it is not feasible to decelerate enough in time (Rule $R_1$).

If the vehicle stops, then pedestrians start crossing. In this case the vehicle queue waiting at the intersection starts increasing in length (Case 4). The vehicle is trying to find a gap between groups of pedestrians and initiates the negotiation if its queue size increases to more than three (Rule $R_7$). If the current lead pedestrian in the group is willing to cross (Rule $R_8$) then they may not yield, in which case the vehicle keeps waiting till the next negotiation opportunity (Rule $R_3$). Otherwise, if the pedestrian yields, the waiting vehicles start moving.

While the vehicles are passing through the intersection and the vehicle flow is heavy, the pedestrian count waiting near the intersection will increase with time (Case 3). Similar to the previous case, the waiting pedestrians will try to negotiate for the right of way. If pedestrians have waited beyond their maximum waiting time or a gap is identified between the vehicle queues, then at this point the lead pedestrian signals the current lead vehicle to stop (Rules $R_6$ and $R_3$). The vehicle may yield if there are no physical constraints to prevent stopping at the start of the intersection, or if the pedestrians show an aggressive behavior (Rule $R_4$). In case the vehicle cannot stop at the intersection, it generates an alert (Rule $R_1$).

However, if a single pedestrian is waiting for the vehicle queue to pass (Case 2), then vehicles can negotiate to continue moving until the waiting time for the pedestrian has exceeded their maximum waiting time, or there are physical constraints that prevent stopping (Rules $R_5$, $R_1$ and $R_2$). The pedestrian yields, but starts negotiating when either their waiting time has exceeded the maximum limit or they identified a gap between the moving vehicles (Rules $R_3$ and $R_6$). In the latter case, the lead vehicle of the next queue accepts to negotiate and slows down for the pedestrians.
5.2.5 **Negotiation examples**

An example negotiation is shown in Fig. 10. At time $t_1$ the pedestrians are waiting for too long (waiting time $> \text{pedestrian's maximum waiting time}$, and thus $Y << NY$). The lead vehicle decides to slow down and stop (Fig. 10a).

---

(a) At time $t_1$

(b) At time $t_i$, $i > 1$

(c) At time $t_{i+j}$, $j > 0$

---

Figure 10: Example scenario: vehicle is finding gap between pedestrian groups.

Meanwhile, there may be new pedestrians appearing closer to the pedestrian group. By the time $t_i$, the lead vehicle has waited for a group of five pedestrians to finish crossing (who have waited beyond their maximum waiting limit and not willing to yield) and the current size of the pedestrian group has increased to eight (Fig. 10b). The vehicle may find a negotiation opportunity here as the sixth pedestrian (highlighted, who joined the moving group later) has not yet stepped
beyond the curb, so the vehicle will initiate negotiation with this current lead pedestrian. The highlighted pedestrian may acknowledge by stopping, in which case an agreement is reached and the vehicle queue starts moving (Fig. 10c). Similarly, pedestrians also find gaps in vehicle queues using the same strategy.

5.3 EXPERIMENT DESIGN

This section describes the simulation environment, different experiment cases to study the proposed negotiation process, and the observables.

5.3.1 Simulation environment

Again, the proposed negotiation model is also simulated using SUMO (Simulation of Urban Mobility) and MATLAB; the simulation is run for around seven hours (24000 steps of 1 s each) for each scenario with varying pedestrian and vehicle flows. Compared to previous chapter, the scenarios are more varied as discussed below. Observations are averaged.

5.3.2 Pedestrian modeling

At different timestamps, pedestrians are introduced into the environment starting at a random distance from the crossing point. By default, the pedestrians approach the curbside with an assumed average walking speed of 1.2 m/s. The pedestrians’ rate of appearance is varying to simulate different density scenarios:

1. High frequency (P_{HF}): Pedestrians appear randomly every 1 s – 4 s for a total of 9603 pedestrians over the 24000 iterations. Group formation is frequent, and the group sizes are larger than in the following cases.

2. Moderate frequency (P_{MF}): Pedestrians appear randomly every 1 s – 10 s for a total of 4395 pedestrians. Group formation is less frequent compared to the previous case, and also the group sizes are moderate in this case.

3. Low frequency (P_{LF}): Pedestrians appear randomly every 1 s – 20 s for a total of 2292 pedestrians. Group formation is even less frequent and group sizes are small.

Again, the gaze and gestures of the pedestrian cannot be modeled in SUMO, and neither the detection of gaze and gestures by vehicles. Instead, the approaching vehicles model an intention value associated with pedestrian behavior at every simulation step. These intention values define the aggressive (Y < NY) or cooperative (Y > NY)
behavior of pedestrians. It is assumed that initially, the pedestrian is approaching towards the intersection with the intention to cross first, so the intention value $Y$ to yield is assigned a low value, $Y = 0.2$ (not set to zero to account for uncertainty). During the negotiation process, the intention value changes in proportion to the change in speed of a pedestrian. To define a group behavior, whenever a pedestrian joins the pedestrian group their intention value changes to that of the lead pedestrian in the group.

5.3.3 Experiment cases

The vehicle flow is also modeled randomly. It is generated by SUMO’s default, a binomial distribution, to approximate a Poisson distribution. For this experiment, two cases of traffic flow density are defined: (i) normal traffic flow $V_{NT}$ (800 vehicles/hour), and (ii) heavy traffic flow $V_{HT}$ (1200 vehicles/hour). The different combinations of vehicle-pedestrian flows are summarized in Table 6. With these cases two types of models are tested: the proposed negotiation model (NM), and the conservative model (CM).

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>Pedestrian frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal traffic</td>
<td>$V_{NT-P_{HF}}$</td>
</tr>
<tr>
<td>Heavy traffic</td>
<td>$V_{HT-P_{HF}}$</td>
</tr>
</tbody>
</table>

Table 6: Vehicle-pedestrian flow combinations

Negotiation model: In the experiments, a vehicle enters the simulation with zero speed and accelerates up to the maximum allowable speed. This is achieved before reaching a distance of around 100m from the intersection (the total lane length before the intersection is 200m in this experiment). It is assumed that interaction starts when the lead pedestrian reaches a distance of 2m or less from the curbside. At this encounter point, the speed of the leader vehicle depends on its distance from the intersection. The parameters recorded at each step of the negotiation are the speed and position of vehicle and pedestrian; the position of the pedestrian also with respect to distance from both lane center and curbside. Few assumptions in the modelling are:

i) The environment is an unregulated road intersection and the vehicles are moving along a straight line on the road; there is no lane changing or passing around the pedestrian.

ii) Vehicles and pedestrians enter and exit the simulation in the same order; there is no overtaking.
iii) The current model considers only the lead vehicle’s interaction with a pedestrian group approaching from one direction and intending to cross the intersection; other road users are not considered.

**Conservative model:** Similar to the previous chapter, the conservative behavior of the vehicle is simulated for comparing the performance of the proposed negotiation model. Again, the conservative behavior of vehicles means that the vehicle always stops whenever any pedestrian is detected within 2m of the curbside. Thus in the conservative model, pedestrians always show an aggressive behavior and keep on moving with the average walking speed, and the vehicle(s) wait until the pedestrian(s) have finished crossing.

5.3.4 Observables

The performance of the proposed negotiation model is measured in terms of traffic disturbance analysis. For each case in each model (negotiation and conservative), the following parameters are observed:

1. *Waiting time for pedestrian group:* The pedestrian group waiting time is computed as the difference in timestamp when the leader pedestrian stopped for the vehicle(s) and the timestamp when the pedestrian group resumes walking.

2. *Waiting time for each vehicle:* Also, the waiting time for each vehicle is computed from the timestamps at which a vehicle enters the simulation environment and crosses the end of the intersection. The difference between the entry and exit timestamps provides the travel time for each vehicle. The waiting time of a vehicle is computed as the difference between the travel time of the vehicle in each model, and its travel time in the case of no interruptions (i.e., crossing the intersection without encountering pedestrians).

3. *Waiting group density:* The waiting group density is defined as the number of pedestrians or vehicles in the pedestrian group or vehicle queue, respectively, during the waiting phase at the intersection. The waiting group density is measured to analyze the pedestrian and vehicle accumulation at the intersection.

4. *Overall intersection throughput:* Throughput is the number of vehicles passing the crossing point per hour. The overall crossing point throughput is calculated as the total number of vehicles which passed the crossing point divided by the simulation run time.
5.4 RESULTS AND DISCUSSION

This section discusses the results of three types of analysis to measure the traffic disturbance: waiting time analysis, accumulation analysis, and the overall throughput analysis at the intersection.

5.4.1 Waiting time analysis

In first part of this analysis, the average waiting time is computed for vehicles and pedestrians, and then compared between the two models. Secondly, the frequency distribution of waiting times for vehicles in both models is discussed to understand the overall flow of traffic. At last, the waiting time pattern of vehicles and pedestrians in the negotiation model is also discussed.

5.4.1.1 Waiting time

For both negotiation and conservative models, the average waiting time of vehicles and pedestrians is computed at the end of the simulation run for each case (2 × 6 entries in Table. 7). In CM, vehicles always stop for pedestrians, so the waiting time for pedestrians is zero and their average waiting time is computed only for the NM (1 × 6 entries in Table. 7). It is clear that the vehicle’s average waiting time is lower in NM in typical traffic conditions, at the cost of some waiting time for pedestrians. However, this waiting time for pedestrians does not exceed those at regulated intersections with predictable average waiting times. The average pedestrian delay measured at signalized intersections is more than 20s for an average cycle time of 90s (Nash-Traffinity, 2014).

Table 7: Waiting time analysis of vehicles and pedestrians for negotiation model (NM) and conservative model (CM)

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>$V_{HT-PHF}$</th>
<th>$V_{NT-PHF}$</th>
<th>$V_{HT-PMF}$</th>
<th>$V_{NT-PMF}$</th>
<th>$V_{HT-PLF}$</th>
<th>$V_{NT-PLF}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle</td>
<td>NM</td>
<td>14.7s</td>
<td>11.8s</td>
<td>6.47s</td>
<td>10.72s</td>
<td>4.53s</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>626.5s</td>
<td>624.6s</td>
<td>92.2s</td>
<td>93.26s</td>
<td>28.75s</td>
</tr>
<tr>
<td>Pedestrian</td>
<td>NM</td>
<td>13.8s</td>
<td>5.64s</td>
<td>8.89s</td>
<td>3.26s</td>
<td>5.69s</td>
</tr>
</tbody>
</table>

**Pedestrian high frequency:** The average waiting time for vehicles is significantly less for negotiating vehicles (14.7s) as compared to the conservative vehicles (626.5s). This difference is maximum for peak traffic conditions (cases $V_{HT-PHF}$ and $V_{NT-PHF}$) when pedestrians and vehicles are appearing in high frequency, and thus have more frequent conflicts at crossing zones. Also, the waiting time for pedestrians is higher (13.8s) in the first case $V_{HT-PHF}$ when compared to other cases. The pedestrian waiting time is much lower when compared to the waiting time of conservative vehicles. However, it is sim-
ilar to the waiting time for negotiating vehicles. This shows that negotiation balances the right of way among vehicles and pedestrians.

**Pedestrian moderate frequency:** For moderate pedestrian frequencies (cases $V_{HT-P_{MF}}$ and $V_{NT-P_{MF}}$), this difference in waiting time for both models is reduced when compared to the above cases, as the number of vehicle-pedestrian interactions decreases. Negotiation performs better in this case as well.

**Pedestrian low frequency:** In this case the chances of a vehicle encountering a pedestrian is low and thus the waiting time for the CM is less as compared to other cases. With a lower pedestrian frequency in heavy traffic conditions ($V_{HT-P_{LF}}$), the NM performs better. However, in normal traffic conditions ($V_{NT-P_{LF}}$) both models converge.

5.4.1.2 **Frequency distribution**

The overall traffic flow (of vehicles) can be understood by the frequency distribution of waiting times for different vehicles. The quantitative distribution of waiting time for vehicles in both models (negotiation and conservative) is shown in Fig. 11. It is clear from the distribution in Fig. 11a and Fig. 11b that in heavy traffic conditions ($V_{HT-P_{HF}}$ and $V_{NT-P_{HF}}$) about 80% of the negotiating vehicles have waited for less than 20s at intersections while 80% of conservative vehicles have considerably longer waiting time exceeding 600s.

In other cases when pedestrian frequency is decreased ($V_{HT-P_{MF}}$ and $V_{NT-P_{MF}}$), around 90% of negotiating vehicles have waiting time of less than 10s as compared to 100s waiting time for 90% of the conservative vehicles (Fig. 11c and Fig. 11d). This analysis supports the hypothesis that negotiation improves the waiting time of vehicles at intersections.

For lower pedestrian frequency with heavy traffic ($V_{HT-P_{LF}}$ and $V_{NT-P_{LF}}$), most of the negotiating vehicles experience much less delay as compared to conservative vehicles (Fig. 11e), while in normal traffic with low pedestrian frequency both negotiating and conservative vehicles experience less waiting time (Fig. 11f).

5.4.1.3 **Traffic movement pattern in negotiation model**

The traffic movement can be understood in terms of the waiting time pattern of vehicles and pedestrians. The waiting time series for vehicles and pedestrians in the negotiation model for a time window of ~200 seconds (out of total 24000s) is shown in Fig. 12.

In the NM, the waiting time for vehicles is high when the waiting time for pedestrians is zero (and vice-versa). This alternating movement pattern of both parties shows the balance of right of way among them (Fig. 12). For the case of highest traffic density ($V_{HT-P_{HF}}$), the height and width of the peaks are maximum as compared to other cases but the decreasing peaks indicate the release of traffic at the
Figure 11: Waiting time frequency distribution in negotiation model (NM) and conservative model (CM)

(a) \( V_{\text{HT}} \) - P

(b) \( V_{\text{HT}} \) - MF

(c) \( V_{\text{HT}} \) - LF

(d) \( V_{\text{NT}} \) - P

(e) \( V_{\text{NT}} \) - MF

(f) \( V_{\text{NT}} \) - LF

INTRODUCING SOCIAL RULES IN NEGOTIATION
5.4 Results and Discussion

![Waiting time patterns for vehicle and pedestrians in different experiment cases](image)

Figure 12: Waiting time patterns for vehicle and pedestrians in different experiment cases.

(a) VHT-PF
(b) VHT-PF
(c) VHT-PF
(d) VNT-PF
(e) VNT-PF
(f) VNT-PF
crossing point from time to time (Fig. 12a). When the vehicle flow is normal with high pedestrian frequency (VNT-PHF), there is a larger number of peaks with less height and width, which shows the more frequent release of traffic (Fig. 12b).

For moderate pedestrian frequency (VHT-PMF and VNT-PMF), a similarly balanced movement pattern is observed for both vehicles and pedestrians but with a lower waiting time (Fig. 12c and Fig. 12d). In case of lower pedestrian frequency (VHT-PLF and VNT-PLF), the waiting time is significantly reduced for both vehicles and pedestrians due to fewer interactions. The peaks in the graph show the traffic movement during a pedestrian encounter with vehicle (Fig. 12e and Fig. 12f). Thus, the above analysis supports the hypothesis that negotiation will improve the coordination among both parties, and the overall traffic flow is smoother for negotiating vehicles as compared to the conservative vehicles.

5.4.2 Waiting group density analysis

The flow of traffic can also be understood in terms of waiting group density of parties near the intersection (accumulation analysis). The queue size-time series (first 200s of simulation) for vehicles and pedestrians in the negotiation model relative to the waiting time series discussed in the previous section are shown in Fig. 13. It is clear from the increasing and decreasing pattern of peaks in the graph that the accumulation of vehicles (caused by waiting for a pedestrian) decreases in the next few seconds once the vehicle has negotiated for the right of way. A similar pattern is observed for the pedestrian queue.

When pedestrian frequency is high and the vehicle flow is heavy then the waiting group density is highest among all cases (case VHT-PHF, Fig. 13a). The vehicle queue size is higher in heavy vehicle traffic cases as compared to normal vehicle traffic cases (Fig. 13a, Fig. 13c, Fig. 13e), while the pedestrian queue size is lower in cases of moderate and low pedestrian frequency (Fig. 13c, Fig. 13d, Fig. 13e, Fig. 13f).

The quantitative waiting queue size distribution in NM and CM in terms of the time fraction for which there is a given number of vehicles in the waiting queue is computed in Table. 8 (6 cases × 8 queue sizes × 2 models entries in the table).

Case VHT-PHF: In NM, about 80% of the time the waiting vehicle queue size is between 8-12 while the queue size is much larger in the CM. The distribution shows that 99.6% of the time in the CM the queue size is between 24-28, which clearly indicates that after a certain point of time the lane gets congested.

Case VNT-PHF: In NM, about 80% of the time the waiting queue size is less than 4 and few times it reaches 8 (about 16%). While in the CM, the waiting queue size does not improve from the previous case (99.4% of the time queue size is between 24-28). This indicates that
Figure 13: Accumulation (waiting queue size) analysis for vehicle and pedestrians in different experiment cases
Table 8: Vehicle queue size distribution for negotiation model (NM) and conservative model (CM)

<table>
<thead>
<tr>
<th>Queue size</th>
<th>Model</th>
<th>$V_{HT}$-P$_{HF}$</th>
<th>$V_{NT}$-P$_{HF}$</th>
<th>$V_{HT}$-P$_{MF}$</th>
<th>$V_{NT}$-P$_{MF}$</th>
<th>$V_{HT}$-P$_{LF}$</th>
<th>$V_{NT}$-P$_{LF}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>NM</td>
<td>0.1%</td>
<td>0.1%</td>
<td>0.2%</td>
<td>0.7%</td>
<td>16.6%</td>
<td>75.7%</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>0.1%</td>
<td>0.1%</td>
<td>0.1%</td>
<td>0.3%</td>
<td>0.6%</td>
<td>70.4%</td>
</tr>
<tr>
<td>4</td>
<td>NM</td>
<td>7.5%</td>
<td>83.5%</td>
<td>34%</td>
<td>94%</td>
<td>45%</td>
<td>24.3%</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>0%</td>
<td>0.1%</td>
<td>0.1%</td>
<td>0.1%</td>
<td>0.9%</td>
<td>19.3%</td>
</tr>
<tr>
<td>8</td>
<td>NM</td>
<td>35.1%</td>
<td>16.2%</td>
<td>64.5%</td>
<td>5.3%</td>
<td>38.2%</td>
<td>20%</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>0%</td>
<td>0.1%</td>
<td>0.1%</td>
<td>0.1%</td>
<td>2.6%</td>
<td>10.3%</td>
</tr>
<tr>
<td>12</td>
<td>NM</td>
<td>43.4%</td>
<td>0.2%</td>
<td>1.3%</td>
<td>0%</td>
<td>0.2%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>0.1%</td>
<td>0.1%</td>
<td>0.1%</td>
<td>0.2%</td>
<td>27.6%</td>
<td>0%</td>
</tr>
<tr>
<td>16</td>
<td>NM</td>
<td>12.6%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>0.1%</td>
<td>0.1%</td>
<td>0.5%</td>
<td>1%</td>
<td>57.6%</td>
<td>0%</td>
</tr>
<tr>
<td>20</td>
<td>NM</td>
<td>1.1%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>0%</td>
<td>0.1%</td>
<td>80.1%</td>
<td>78.8%</td>
<td>10.6%</td>
<td>0%</td>
</tr>
<tr>
<td>24</td>
<td>NM</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>49.3%</td>
<td>49.4%</td>
<td>19%</td>
<td>19.6%</td>
<td>20%</td>
<td>0%</td>
</tr>
<tr>
<td>28</td>
<td>NM</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>CM</td>
<td>50.3%</td>
<td>50%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
</tbody>
</table>

In both these cases the vehicle waiting queue reaches the maximum capacity of the lane and results in congestion.

Case $V_{HT}$-P$_{MF}$: In NM, about 98% of the time the waiting queue size is between 4-8 (reduced as compared to the first case), and in this case, for CM the queue size is 20 for 80% of the times.

Case $V_{NT}$-P$_{MF}$: The distribution for the CM, in this case, is similar to the previous case, but the NM shows improved performance as the queue size is less than 4 for 94% of the time.

Case $V_{HT}$-P$_{LF}$: In case of the NM, about 17% of the time the queue size is zero and 45% of the time, it is less than 4. The waiting queue size is reduced in this case for the CM as well, as 90% of the time the queue size is between 12-16 and the maximum queue length is around 20.

Case $V_{NT}$-P$_{LF}$: In this case, the waiting queue size is reduced significantly and both models converge. About 75% of the times the queue size is zero in NM as compared to 70% of the times for CM, and for the rest of the time, the queue size is less than 4. Thus, in this case, there is no significant difference between the models.

For higher pedestrian frequency cases, about 80% of the time the waiting vehicle queue size is between 8-12 in NM, while the queue size is much larger in the CM. The distribution shows that 99.6% of the time in the CM the queue size is between 24-28, which clearly indicates that after a certain point of time the lane gets congested. While for moderate pedestrian frequency, the NM performs even better with a waiting queue size of around 4 for more than 90% of the time and CM still does not show much improvement in congestion (waiting queue size around 20 for 80% of the time).
However for normal traffic and low pedestrian frequency (Case $V_{NT-P_{LF}}$), the waiting queue size is reduced significantly and both models converge. About 75% of the time the queue size is zero in NM as compared to 70% of the time for CM, and for the rest of the time, the queue size is less than 4. Thus, in this case, there is no significant difference between the models. By reducing the amount of congestion on roads, the overall traffic flow is reduced in the negotiation model when compared to the conservative model. These results of accumulation analysis support the hypothesis.

5.4.3 Throughput analysis

The number of vehicles per hour crossing the intersection in different experiment cases for the negotiation (NM) and conservative (CM) model is listed in Table 9.

<table>
<thead>
<tr>
<th></th>
<th>$V_{HT-P_{HF}}$</th>
<th>$V_{NT-P_{HF}}$</th>
<th>$V_{HT-P_{MF}}$</th>
<th>$V_{NT-P_{MF}}$</th>
<th>$V_{HT-P_{LF}}$</th>
<th>$V_{NT-P_{LF}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>NM</td>
<td>1187</td>
<td>800</td>
<td>1195</td>
<td>800</td>
<td>1195</td>
<td>800</td>
</tr>
<tr>
<td>CM</td>
<td>140</td>
<td>140</td>
<td>667</td>
<td>664</td>
<td>1139</td>
<td>800</td>
</tr>
</tbody>
</table>

In the NM for heavy traffic scenarios, almost all the vehicles that were introduced in the simulation passed (throughput $\approx 1200 \text{ veh/hour}$). For high pedestrian frequency, the throughput in the conservative model is only 140 veh/hour (about 12% of the throughput in negotiation model) which increased up to 667 veh/hour (about 50% of the throughput in negotiation model) with moderate pedestrian frequency. While in case of low pedestrian frequency, the throughput for both models is the same and almost equal to the regular vehicle flow. It is clear then, that more vehicles are passing through the intersection in the NM, which supports the hypothesis.

Normal traffic scenarios ($V_{NT}=800 \text{ veh/hour}$): In CM, the throughput is the same as in the previous case for high and moderate pedestrian frequency, which indicates that the lane becomes congested after some time, while the NM improves the throughput to the regular flow level. In case of low pedestrian frequency, the throughput for both models is the same and almost equal to the regular vehicle flow.

5.5 Conclusions

This chapter presented a negotiation model between groups of pedestrians and self-driving vehicles and is implemented using SUMO and MATLAB. The informal social rules of negotiations in a complex scenario are conceptualized and then formulated as negotiation strategies. The negotiation framework takes into account the effect of social
rules on pedestrians’ behaviors, and further demonstrate their ability to give vehicles a fair chance to pass first in certain situations. This research answers the related research questions in this chapter.

Dynamic behavior of groups of pedestrians who interact with a random flow of vehicles is simulated and tested for different traffic conditions by varying the frequency of agents in the simulation. The experiments present more complex interaction situations compared to previous chapter. This simulation study shows the potential of negotiations with social rules to reduce the estimated congestion problems due to conservative self-driving vehicles in presence of multiple vehicles and pedestrians.

Compared to previous model (Chapter 4), the average waiting times of both parties increased in peak hours due to more frequent encounters among them. However, the simulation results support the hypothesis of this research that negotiations will improve the waiting time of vehicles and the overall throughput at intersections, thus, maintaining a smoother flow of traffic. The waiting time and accumulation analysis results also reveal the movement patterns of vehicles and pedestrians, showing a balanced right of way among them. Results also reveal the adverse impact of the conservative design of self-driving vehicles on the traffic flow, producing longer waiting queues during peak traffic hours.

The social rules concept presented in this chapter is limited to interaction among groups. The proposed model is based on the assumption that every pedestrian and vehicle follows the actions of their leaders which may not always be the case in real life scenarios. The focus of the next work is to eliminate this assumption and expand the model considering individual decision-making of pedestrians.
This chapter is based on the article “Pedestrian’s risk-based negotiation model for self-driving vehicles to get the right of way” published in the journal Accident Analysis and Prevention by Gupta, Vasardani, Lohani, and Winter (2019). As such, most of the content in this chapter is compiled from this publication. My contribution as a first author in this work includes proposing the research problem and hypothesis; developing the model; designing experiments and performing the analysis; evaluating the hypothesis; and also providing related discussions and conclusions. The entire work was supervised by my supervisor Prof Stephan Winter, and co-supervisor Dr Maria Vasardani, and external supervisor Prof Bharat Lohani, who actively provided their suggestions and feedback at each stage of this research.

6.1 INTRODUCTION

This research further extends the previous model to overcome the assumptions of group behavior. The model allows for multiple vehicles and multiple pedestrians, individual decision making, and different personalities, following some social rules. The possible negotiation opportunities for vehicles are modeled considering different risk-taking behaviors of pedestrians. This work particularly focuses on introducing a pedestrian’s risk-based model for negotiation between multiple vehicles and multiple pedestrians. The following research question from Section 1.3 is addressed in this chapter – Does pedestrian’s risk-averse attitude along with the influence of social rules increase the chances of successful negotiations for self-driving vehicles?

The model is tested against the same overarching hypothesis – the vehicle’s chances for the right of way increase with negotiation, which will consequently reduce their average waiting time and improve the overall throughput at intersections when compared to the vehicle’s conservative behavior. Also, the simulation environment is the same (SUMO and MATLAB), but with different experiment settings. In the experiments, the waiting times of vehicles and the intersection throughput are analyzed for different distributions of risk-averse and risk-taking pedestrians in the pedestrian flow. These parameters are then compared to the conservative behavior model in which vehicles are slowing down when sensing pedestrians intending to cross the road.
The implemented negotiation model demonstrates how negotiations with risk-averse pedestrians improve the flow of vehicles. Compared to the conservative model, the waiting time of the vehicles is significantly improved in the negotiation model when the chances of encountering a risk-averse pedestrian are high. The results show that the overall average waiting time and intersection throughput is improved with negotiations even in the case of fewer risk-averse pedestrians in the pedestrian flow. Thus, the contributions in this chapter are:

- an improved negotiation model between multiple self-driving vehicles and multiple pedestrians allowing individual decision-making;
- the consideration of different risk-taking attitudes of pedestrians in order to improve vehicle throughput without compromising safety.

6.2 RISK-BASED VEHICLE-PEDESTRIAN NEGOTIATION MODEL

Similar to the previous models, the negotiation is conceptualized as a process in which both parties—vehicles, and pedestrians—take steps to agree on an outcome, i.e., on who has the right of way to pass the conflict point first. Also, every party seeks to make that outcome favorable to them, i.e., minimize the waiting time considering the risk involved.

The interaction environment is any unmarked location along the road network where at least one passenger shows intend to cross. This intention can happen at unmarked intersections, or the pedestrian can consider jaywalking. In the implementation of the proposed model, an unmarked intersection is assumed, where pedestrians approach the road of the vehicle from the intersecting road (Fig 14). Pedestrian and vehicle trajectories can be extrapolated from their current location, speed, and heading. These extrapolated trajectories will be on collision or near collision with the vehicle considering its options. For these selected pedestrians a negotiation must entail. In this work, this factor is called as risk (of collision). It can be implemented for example by a simple linear model which is discussed in Section 6.2.1.

Negotiation also depends on the risk-taking attitude of pedestrians towards vehicles. Pedestrians may or may not accept the street-crossing risk when the vehicle is approaching from a conflicting direction. The perception of a safe gap from the vehicle is individually different (Cohen, Dearnaley, and Hansel, 1955); few people tend to take higher risks than others. Pedestrian behavior, in literature, is studied as two types: a risk-taking pedestrian who is willing to cross first when confronted with a vehicle, and is less likely to yield; another type is a
risk-averse pedestrian who is likely to yield to the vehicle as they are not willing to accept the risk. This model considers these two types of pedestrian behaviors during negotiation. However, this pedestrian behavior is dynamic and is often influenced by other social factors\(^1\). This change in behavior is also considered in the proposed model which is further discussed in Section 6.2.2. After discussing the implementation details of pedestrians’ risk and behaviors in this model, this section then describes the possible negotiation cases based on the risk to a pedestrian (Section 6.2.3). This is followed by a description of the overall proposed conceptual model of negotiation (Section 6.2.4).

![Figure 14: Interaction scenario with pedestrian’s risk computation](image)

### 6.2.1 Pedestrian risk computation

The situation studied here is depicted in Fig 14. The conflict point, represented by red dots in Fig 14, is where the pedestrian’s trajectory intersects with the vehicle’s trajectory. At any instance, \( t_v \) denotes the current predicted time required by the vehicle to reach the conflict point, and \( t_{pi} \) denotes the current predicted time required by the \( i \)th pedestrian to reach the same point. These times can be estimated with their current locations, speeds, and headings.

Different pedestrians intending to cross the road are at different degrees of risk of collision with the vehicle. This risk depends on the overlap in their predicted time to reach the conflict point \( (t_{pi}) \) with that of the approaching vehicle \( (t_v) \). Moreover, it also depends on the total time taken by the pedestrians to walk from the starting edge of the intersection until the end of the lane crossing (denoted by crossing time \( c \)).

In this model, the risk to each pedestrian is mapped in the range \([0,1]\). As represented in Fig 14, this risk linearly increases if the pedestrian is expected to reach a location between the starting edge of the intersection and the conflict point, when the vehicle is expected to pass the conflict point \( (t_p > t_v) \). Similarly, the pedestrian’s risk decreases if the pedestrian is expected to pass the conflict point but is still before the end of the lane edge \( (t_p < t_v) \). The risk to a pedestrian

---

1 Studies in behavioral psychology have identified the factors influencing the social behavior of pedestrians (Harrell, 1991; Ishaque and Noland, 2008)
is maximum (= 1) if their time to reach the conflict point is the same as that of the approaching vehicle \((t_p = t_v)\), i.e., a collision is imminent if none of the parties changes their behavior. The risk is zero if the difference in their arrival times is greater than the crossing time \(c\) of pedestrians. Thus, the pedestrians are at no risk when either they are expected to finish crossing before the vehicle reaches the conflict point, or if the vehicle will pass before they arrive near the curbside. Hence the risk\(^2\) to a pedestrian is formulated as in Eq 1

\[
\text{risk} = \begin{cases} 
    1 - \frac{t_v - t_p}{c/2}, & t_p < t_v \\
    1 - \frac{t_p - t_v}{c/2}, & t_p \geq t_v \\
    0, & |t_v - t_p| \geq c/2
\end{cases}
\] (1)

Note that the vehicle and pedestrian are considered as point objects for risk computations, and the width of the vehicle is not taken into account. In the latter case, the risk mapping can be done by considering a conflict zone instead of a conflict point which doesn’t change the concepts presented here. Also, this work assumes that pedestrians are walking at a constant speed. Negotiation is a continuous process until an agreement is reached which is explained in detail 6.2.4 This means that the risk to a pedestrian is re-assessed at every timestep which captures any changes in the pedestrian’s behavior at the next instance, including any change in their walking speed or in their action to stop at the curb for safety reasons. So assuming a constant walking speed for pedestrians until they stop doesn’t affect the model.

6.2.2 Pedestrian behavior

In reality, people (even risk-averse), have limited patience. Literature has shown that with growing waiting time they become impatient (Li, 2013, 2014). Empirical studies on pedestrians’ waiting times have found that their impatience and risk-taking behavior increase after 20s of delay (Kaiser, 1994). Similarly, even risk-taking pedestrians do not want to compromise their safety and consider physical constraints before taking a decision to cross (Li, 2014). Pedestrians may also be affected by the behavior of others at crossings; they are more likely to cross if pedestrians next to them have started crossing (Faria, Krause, and Krause, 2010).

In this research, every pedestrian is categorized based on their risk-taking behavior as either risk-taker (RT) or a risk-averse (RA). A risk-taking pedestrian is not willing to yield to the approaching vehicle unless the vehicle has notified an alert that it cannot stop in time.

\(^2\) The metric quantifies the risk of conflict based on the current position and speed of vehicle and pedestrian, rather than presenting an actual probability of impact.
(called as alert status of the vehicle). In the latter case, every pedestrian waits for the vehicle to pass. A risk-averse pedestrian, in general, waits and yields to the vehicle when the risk to them is high. However, risk-averse pedestrians do not wait longer than their maximum waiting time limit (around 20s) and trigger a stepping out action after this time. This model also assumes that if there is any risk-taker next to them who sets off first, then a risk-averse pedestrian will start following them. In such situations, if physical constraints do not allow the vehicle to stop before time, then it notifies the pedestrians through an alert. Else, the vehicle slows down.

6.2.3 Possible negotiation opportunities for vehicle

The possible actions by the vehicle for different degrees of perceived risk to the pedestrians are shown in Table 10. If the risk to the pedestrian is zero, then there is no negotiation required and both parties can move with their current or maximum speed. As the approaching vehicle and pedestrians come closer to the conflict point with time, the risk to the pedestrians starts increasing (risk > 0). Initially, when the risk is low (< 0.5), the vehicle keeps moving at the current speed while monitoring the movement of pedestrians. However, when the overlap in the time of arrivals of both parties increases, the risks to pedestrians also increases (risk ≥ 0.5).

Table 10: Possible cases of risk to the pedestrians and corresponding action by the vehicle in that situation

<table>
<thead>
<tr>
<th>Pedestrian’s risk</th>
<th>Action by the vehicle</th>
</tr>
</thead>
<tbody>
<tr>
<td>risk = 0</td>
<td>no negotiation required, vehicle keeps accelerating until it attains the maximum speed</td>
</tr>
<tr>
<td>0 &lt; risk &lt; 0.5</td>
<td>vehicle keeps moving with the current speed and monitors the pedestrian’s action</td>
</tr>
<tr>
<td>risk ≥ 0.5</td>
<td>vehicle starts negotiating as follows:</td>
</tr>
<tr>
<td></td>
<td>(a) if (alert by vehicle) then vehicle moves</td>
</tr>
<tr>
<td></td>
<td>(b) if (pedestrian is RA) then vehicle moves</td>
</tr>
<tr>
<td></td>
<td>(c) if (pedestrian is RT) then vehicle slows down</td>
</tr>
</tbody>
</table>

The traffic situation at any time will be a mix of pedestrians who are at different degrees of risk – some may be at high risk and few may be at no risk. The vehicle, however, can only broadcast a common signal to the approaching pedestrians, so it waits until there are only high-risk pedestrians near the curb side to negotiate with. In the implementation of this process, if some pedestrians moving ahead in the crowd are at no risk, then the vehicle waits to broadcast its negotiation request till they finish crossing. Once the zero-risk pedes-
trians have finished crossing, the vehicle broadcasts its negotiation request to those at risk. At this stage, if the vehicle cannot stop then it broadcasts the message to pass first and notifies an alert status to the pedestrians. Else, negotiation by vehicle depends on the behavior of the pedestrians at risk. The vehicle has an opportunity to pass first if the pedestrian is risk-averse (RA) who hesitates to take the high risk. However, if any pedestrian (at risk) is a risk-taker then they are tempted to cross first despite being in a risky situation. In the latter case, the negotiation request by vehicle is ignored or rejected by a risk-taker and the vehicle yields to the pedestrians. In the next section, the overall stepwise negotiation process is discussed which is followed by a simulation example to explain the proposed model.

### 6.2.4 Conceptual negotiation model

The previous conceptual model for negotiation is extended to a risk-based model and is presented in Fig 15. This model shows the negotiation of a vehicle with the $i^{th}$ pedestrian at a time instance $t$. It is assumed that the vehicle’s intentions are broadcasted as a common signal to all the competing pedestrians in the scene. The vehicle estimates the model parameters for every pedestrian in the scenario who is competing for the right of way. The first step of communication and detection of parties remains same as the previous model. In the next step, the vehicle first checks for any trajectory conflict with the pedestrian. If there is no conflict then there is no need for any negotiation, else the following steps apply:

1. **Estimate risk to pedestrian**: In case of a potential trajectory conflict, next the vehicle estimates the risk to the pedestrian using Eq. 1 as described in Section 6.2.1. If the risk is zero or less than 0.5
(low risk), then the vehicle acts as described in Table 10. However, if the pedestrian is at a higher risk then the vehicle has to know the intention of the pedestrian.

2. **Predict intention and behavior of the pedestrian:** The vehicle estimates the pedestrian’s intention based on the perceived pedestrian parameters. The intention of a pedestrian, in this model, is represented in terms of chances of them yielding \((Y)\) and not yielding \((NY = 1 - Y)\) to the vehicle. This intention value gives an idea to the vehicle whether the pedestrian is risk-averse (RA when \(Y \gg NY\)) or a risk-taker (RT when \(NY \gg Y\)). In case the vehicle is unsure about this behavior, it falls back to the safety principle and eventually slows down.

3. **Is there an agreement?** The vehicle is continuously looking for an agreement with the pedestrian. An agreement in the negotiation is reached when the intentions of the two parties match. For a vehicle-favored negotiation, matching intentions means that the pedestrian has indicated to stop for the vehicle when the vehicle intended to pass first. Conversely, a negotiation in favor of the pedestrian intending to cross first requires that the vehicle indicates to slow down (intentions of both parties matched). However, if both parties have conflicting intentions to get the right of way first then the vehicle has to start negotiating.

4. **Negotiation:** At this stage, the vehicle has an opportunity to negotiate as the pedestrian is at risk. This, however, depends on the behavior of the pedestrian. The behavior depends on the pedestrian types and is influenced by social rules and physical constraints; all this is already discussed in Section 6.2.2. Based on the vehicle’s perceived behavior of a pedestrian (in Step 2), it decides to move or slow down as discussed in Table 10.

5. **Action mapping:** After this step, both parties indicate their intentions in the form of some signal\(^3\) and the negotiation cycle continues until an agreement is reached. At the next instance, there may be a change in the intentions of any party. For example, a pedestrian may slow down and gesture to stop (acknowledging the vehicle’s right of way request), in which case an agreement is reached, and the vehicle passes first. If there is no acknowledgment from either side, the negotiation cycle continues to seek an agreement till it is safe to do, else the vehicle prepares to slow down.

---

\(^3\) As described in Chapter 4
6.2.5 Example scenario

Two negotiation scenarios are presented below. The negotiation process is discussed for each of them. In these examples, six pedestrians are approaching the intersection ordered by their time of arrivals at the intersection: P1, P2, ..., P6. The vehicle is approaching the intersection from another direction. These examples show the risk to each pedestrian at different timestamps as the vehicle approaches the conflict point, along with the estimated time taken by them to reach that point ($t_p$ and $t_v$).

**CASE 1: ENCOUNTERING RISK-averse PEDESTRIANS** Suppose these pedestrians are risk-averse. Initially, no negotiation is happening as risk is zero for pedestrians in front of the queue (P1 and P2) and they have not yet finished crossing (Fig 16). Meanwhile, the vehicle keeps accelerating if its speed is not maximum. For pedestrian P3, the risk is high, but all parties keep moving as the vehicle is not negotiating yet.

![Figure 16: Interaction example with risk-averse pedestrians at time $t = 8s$](image1)

![Figure 17: Interaction example with risk-averse pedestrians at time $t = 12s$](image2)

When P1 and P2 have finished crossing (Fig 17, the vehicle starts negotiation as P3 is at a high risk ($\text{risk} > 0.5$). The negotiation message is broadcasted by the vehicle to the pedestrians (who have not yet started crossing).

These pedestrians (including P3) are risk-averse, so P3 signals to yield to the vehicle and stops, and the other pedestrians being risk
averse also stop (Fig 18). The vehicle broadcasts the message that it is speeding up to pass first (agreement), and the vehicle passes through the intersection in the next few seconds (Fig 19).

**Case 2: Encountering Risk-Taking Pedestrians** In the same example after Step 2 in Fig 18, if P3 is a risk-taker then the situation is different. P3 takes a risk and keeps moving towards the intersection with the intention to cross first. This movement signal from the pedestrian forces the vehicle to slow down or even to stop (Fig 20).

The slowing down of the vehicle reduces the risk to other approaching pedestrians P4 and P5 who were also at high risk before (they were walking closely behind P3). Whether these pedestrians are risk-takers or risk-averse, the slowing down signal from the vehicle encourages them (P4 and P5) to cross with P3. Now P6 is far behind.
Figure 21: Interaction example with risk-taking pedestrians at time $t = 25s$

P5 due to the temporal gap, so the vehicle still has an opportunity to negotiate with P6. In this example, since P6 is also a risk-taker who is not willing to wait so the vehicle continues to wait until P6 finishes crossing.

In the above examples for the same interaction scenarios but different types of pedestrian behavior, the exit timestamps of the vehicle differ by about 8s. This is a simple example. The experiment design to test the research hypothesis, in the next section, aims to assess the overall traffic flow when a number of vehicles are interacting with a mix of RA and RT pedestrians.

6.3 EXPERIMENT DESIGN

Similar to the previous chapters, the proposed negotiation model is simulated using SUMO and MATLAB. Again, the simulation runtime is around seven hours (24000 steps of 1s each) for each of the experiment cases. Few assumptions in the design are:

1. The environment considered is an unregulated road intersection and the vehicles are moving along a straight line on the road; there is no lane changing or passing around the pedestrian.

2. Vehicles enter and exit the simulation in the same order; there is no overtaking.

3. The current model considers only the vehicle’s interaction with the pedestrians approaching from a conflicting direction whose goal is to cross the intersection; other road users are not considered.

This section further explains the interaction environment, model implementation, pedestrian behavior modeling, different experiment cases, and observables in the simulation.
6.3.1 Interaction environment

An unmarked intersection is set up in SUMO as shown in Fig 22. The length of the lane on which vehicle moves, from the start of the lane to the intersection, is 200m in this experiment. The pedestrian lane is meeting at the intersection which is orthogonal to the vehicle lane.

![Image of SUMO simulation](image)

Figure 22: The interaction environment setup in SUMO. This is a zoomed view of the scene. The lane actually starts from a distance of 200m from the right.

The vehicle and pedestrian behavior is modeled as a free flow. For this experiment, a flow of vehicles at the rate of 1200 vehicles/hour is generated in SUMO. This flow is by default the maximum flow allowed in SUMO; flow is binomially distributed, approximating a Poisson distribution.

6.3.2 Negotiation model

The vehicle starts accelerating from a zero speed at the start of the lane and achieves a maximum speed at a distance of about 100m from the intersection. The parameters recorded at each simulation step are speed and position of the vehicle and pedestrian, along with their respective distances from both lane center and curbside. The risk to each pedestrian in the scene is also computed at each simulation step. Also, the behavior type of the pedestrian is recorded which is discussed in Section 6.3.4. The interaction starts, and the negotiation workflow applies when the pedestrian’s risk becomes greater than zero.

6.3.3 Base model for comparison

Similar to the previous chapters, the performance of the proposed model is compared to the conservative behavior model. In the implementation of this model, the vehicle prepares to stop whenever a pedestrian is detected within 2m from the curbside. The pedestrians
keep on moving with the average walking speed, and the vehicle(s) waits until the pedestrians have finished crossing.

6.3.4 Pedestrian behavior modeling

The pedestrian flow is generated by introducing pedestrians in the simulation environment at different timestamps. Every pedestrian starts walking from a random distance from the conflict point with an assumed average speed of 1 m/s. Also, the waiting time limit for each pedestrian is randomly chosen from a normal distribution with mean waiting time of 20 s and standard deviation 3.33 s (reasons already discussed in Section 6.2.2). The following two types of pedestrian flow are generated for different experiments:

(a) Pedestrian high-frequency (PHF): The pedestrian flow, in this case, is generated by varying the pedestrian rate of appearance in the simulation between 1 s and 10 s. With this frequency, the negotiation model is tested by vehicles’ interaction with a total of 4382 pedestrians at the end of the simulation.

(b) Pedestrian low-frequency (PLF): In another experiment, the pedestrian appearance in the simulation is randomly assigned between 1 s and 20 s, generating a total of 2273 pedestrians.

Rather, the vehicle’s understanding of the pedestrian behavior (RA or RT) is modeled by associating a binary value with each pedestrian (RA = 1, RT = 0). In a real-world implementation of this model, the human behavior prediction algorithms will predict the behavior of pedestrians, which is out of the scope of this work. The experiment cases with different distributions of RA and RT in a pedestrian flow are discussed in the next section.

6.3.5 Experiment cases

The cases for different distributions of risk-averse (RA) and risk-taking (RT) pedestrians are as follows:

1. With 80% risk-averse pedestrians (RA80): In simulations, the pedestrian flow is generated by assigning the risk-averse (RA) behavior to a pedestrian with a probability of 0.8, and a risk-taking (RT) behavior with a probability of 0.2. Thus, there are 80% chances that a vehicle will encounter a risk-averse pedestrian, while only 20% chances of encountering a risk-taker.

2. With 50% risk-averse pedestrians (RA50): Here the probability of assigning a risk-averse (RA) or risk-taking (RT) behavior to a pedestrian is 0.5 each in the simulation.
3. With 20% risk-averse pedestrians (RA20): In this case the probability of assigning the risk-averse (RA) behavior to a pedestrian is reduced to 0.2 while the probability of assigning a risk-taking (RT) behavior is increased to 0.8.

Each of the above cases with different frequencies of pedestrian flow forms six different experiment cases, represented as following: PHF-RA80, PHF-RA50, PHF-RA20, PLF-RA80, PLF-RA50, and PLF-RA20. The performance of the proposed model is tested for these six experiment cases against the conservative model.

6.3.6 Observables

The timestamps at which a vehicle enters the simulation environment (entry) and crosses the end of the intersection (exit) are recorded for each vehicle. Similarly, the entry and exit timestamps of each pedestrian are also recorded. The difference between the entry and exit timestamps provide the travel or walking time for each vehicle and pedestrian respectively. The following parameters are observed for each experiment case at the end of the simulation:

1. Waiting time of each vehicle: For each vehicle, the waiting time in both models is computed as the difference between the observed travel time of the vehicle, and its travel time without encountering any pedestrians.

2. Waiting time of each pedestrian: Similarly for each pedestrian in the negotiation model, the waiting time is computed as the difference between the observed walking time of the pedestrian, and their travel time when there are no interruptions. There is no waiting for pedestrians in the conservative model.

3. Intersection throughput: The intersection throughput is defined as the number of vehicles passing the conflict point per hour. The overall throughput is computed by dividing the total number of passed vehicles at the end of the simulation, by the total simulation run time.

6.4 RESULTS AND DISCUSSIONS

Two types of analysis were performed: waiting time analysis of vehicles and pedestrians and overall intersection throughput analysis. The different experiment cases in the negotiation model (NM) are compared to the results of conservative model (CM).
6.4.1 Waiting time analysis of vehicles

The average waiting time of vehicles is computed at the end of each simulation run in each case. Next, the histogram representations are used to assess the central tendency and variability of the waiting time distributions. Lastly, a cumulative distribution graph of waiting times is discussed and compared among different experiment cases.

**Waiting time statistics** The waiting time statistics are recorded below in Table 11. The results show that the average waiting time of vehicles in NM is significantly lower compared to the CM. For high pedestrian frequency with 20% risk-averse pedestrians (case PHF-RA20), the average waiting time of vehicles is 44.3s, compared to an average waiting time of 95.3s for conservative vehicles. In this case, 50% of the total negotiating vehicles are delayed by less than 20s, while most of the conservative vehicles experienced a delay of 99s. Moreover, the negotiations have further reduced the average waiting times to 4.2s and 0.9s in the presence of more risk-averse pedestrians (cases PHF-RA50 and PHF-RA80, respectively). Even for a low pedestrian frequency, the NM performs better with an average waiting time of less than 4s compared to 28.7s in CM.

Table 11: The vehicles’ waiting times statistics (in sec) for different experiment cases.

<table>
<thead>
<tr>
<th></th>
<th>PHF-RA20</th>
<th>PHF-RA50</th>
<th>PHF-RA80</th>
<th>CM-PHF</th>
<th>PLF-RA20</th>
<th>PLF-RA50</th>
<th>PLF-RA80</th>
<th>CM-PLF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean/SD</td>
<td>44.3/57.40</td>
<td>4.2/2.54</td>
<td>0.95/1.52</td>
<td>95.32/14.34</td>
<td>3.83/10.23</td>
<td>1.32/2.54</td>
<td>0.71/1.09</td>
<td>28.79/9.98</td>
</tr>
<tr>
<td>Median</td>
<td>20</td>
<td>1</td>
<td>1</td>
<td>95</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>29</td>
</tr>
<tr>
<td>Mode</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>99</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>31</td>
</tr>
</tbody>
</table>

Furthermore, the distributions in CM (in both high and low pedestrian frequency experiments), are close to a normal distribution centered around the mean waiting time as discussed above in the respective cases (Fig 23d and 23h). However in NM, the histogram plots of the waiting times of vehicles reveal a right-skewed distribution for all experiment cases (Fig 23a-23c and Fig 23e-23g). The right tails of these distributions suggest that a few vehicles are long delayed compared to others. The number of such vehicles with large waiting times is more in case of high pedestrian frequency compared to cases with lower pedestrian frequency.

**Cumulative distribution function (CDF) graph** The waiting time pattern in the corresponding cumulative distribution graphs (Fig 24) is more interpretable. It can be observed that few negotiating vehicles (case PHF-RA20) waited longer than the conservative vehicles (>20s). This is a result of the accumulation of waiting pedestrians for a long time before they exceeded their waiting limits and started crossing. Another reason is the waiting pedestrians’ tendency...
Figure 23: Density graph for the waiting time data of vehicles recorded in different experiment cases in the negotiation model (a-c, e-g), and in the conservative model (d,h).
to follow a risk-taker, so frequent encounters with a risk-taker are also causing few vehicles to wait longer. In such situations, the temporal gap between arrival times of pedestrians decreases and the chances of risk-taking behavior among pedestrians increases. In these cases, the vehicles have to wait longer for a negotiation opportunity.

Figure 24: Cumulative distribution function (CDF) graph for waiting times of vehicles in different experiment cases.

**Frequency Distribution** The above results suggest that behavior of pedestrians and their frequency of appearance had a significant impact on the vehicles’ waiting times. This is also supported by the quantitative analysis of waiting time distributions presented in Table 12 and Table 13. The results suggest that if the chances of encountering a risk-averse or risk-taker pedestrian are equal (case PHF-RA50), then negotiations can reduce the waiting times up to 20s for 95% of the traffic. On the other hand, when the vehicle encountered risk-taking pedestrians frequently (which is case PHF-RA20 here) then around 30% of the total vehicles waited for more than 100s. However, the reduced waiting times for other 70% vehicles is a result of vehicles’ negotiation achieved with fewer (in this case 20%) risk-averse pedestrians.

Table 12: Waiting time frequency distribution of vehicles for different experiment cases when pedestrian frequency is high.

<table>
<thead>
<tr>
<th></th>
<th>0s</th>
<th>&lt; 10s</th>
<th>&lt; 20s</th>
<th>&lt; 50s</th>
<th>&lt; 100s</th>
<th>&lt; 200s</th>
<th>&lt; 300s</th>
</tr>
</thead>
<tbody>
<tr>
<td>PHF-RA20</td>
<td>10.11%</td>
<td>31.39%</td>
<td>8.86%</td>
<td>17.94%</td>
<td>17.04%</td>
<td>11.99%</td>
<td>2.64%</td>
</tr>
<tr>
<td>PHF-RA50</td>
<td>31.05%</td>
<td>57.68%</td>
<td>6.37%</td>
<td>4.54%</td>
<td>0.35%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>PHF-RA80</td>
<td>48.64%</td>
<td>51.10%</td>
<td>0.25%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>CM</td>
<td>0%</td>
<td>0.11%</td>
<td>0.09%</td>
<td>0.30%</td>
<td>65.11%</td>
<td>34.39%</td>
<td>0%</td>
</tr>
</tbody>
</table>

This table shows that even fewer successful negotiation opportunities for the vehicles would allow the frequent release of vehicles through the intersection, thus reducing the possible congestion on roads. In contrast, the conservative vehicles have to wait until a safe
6.4 RESULTS AND DISCUSSIONS

Table 13: Waiting time distribution of vehicles for different experiment cases when pedestrian frequency is low.

<table>
<thead>
<tr>
<th></th>
<th>0s</th>
<th>&lt; 10s</th>
<th>&lt; 20s</th>
<th>&lt; 50s</th>
<th>&lt; 100s</th>
<th>&lt; 200s</th>
<th>&lt; 300s</th>
</tr>
</thead>
<tbody>
<tr>
<td>PLF-RA20</td>
<td>3.66%</td>
<td>60.65%</td>
<td>2.62%</td>
<td>2.55%</td>
<td>1.40%</td>
<td>0.11%</td>
<td>0%</td>
</tr>
<tr>
<td>PLF-RA50</td>
<td>44.46%</td>
<td>54.27%</td>
<td>0.83%</td>
<td>0.44%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>PLF-RA80</td>
<td>53.65%</td>
<td>46.27%</td>
<td>0.09%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>CM</td>
<td>0.28%</td>
<td>3.02%</td>
<td>17.04%</td>
<td>78.14%</td>
<td>1.53%</td>
<td>0%</td>
<td>0%</td>
</tr>
</tbody>
</table>

gap from the pedestrians is identified which leads to traffic congestion when the frequency of pedestrians is high. Also, the overall traffic movement is improved through negotiations with reduced waiting time for vehicles, compared to the conservative model.

6.4.2 Waiting time analysis of pedestrians

The reduced waiting time for vehicles in NM is at the cost of some waiting time for pedestrians which is discussed in this section. Similar to the previous analysis of vehicle waiting times, the following section discusses the average waiting times of pedestrians, and also a comparison of their distributions in different cases.

Waiting time statistics

The waiting time statistics for pedestrians are recorded in Table 14. In case of simulation with 80% risk-averse pedestrians, their average waiting time is 13.2s. It shows that a risk-averse pedestrian is most likely to wait for not more than 14s. This number is even less than the pedestrians’ intended average waiting times observed in various empirical studies (Kaiser, 1994; Li, 2013) on pedestrian behaviors. Moreover, their waiting time is significantly less compared to the waiting time of vehicles. Thus, the pedestrians’ compromise on waiting times during negotiations can reduce the future traffic congestion problems, also increasing their coordination with self-driving vehicles on roads.

Table 14: The pedestrians’ waiting times statistics (in sec) for different experiment cases.

<table>
<thead>
<tr>
<th></th>
<th>PHF-RA20</th>
<th>PHF-RA50</th>
<th>PHF-RA80</th>
<th>PLF-RA20</th>
<th>PLF-RA50</th>
<th>PLF-RA80</th>
<th>CM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean/SD</td>
<td>5.86/10.84</td>
<td>8.23/8.43</td>
<td>11.93/8.31</td>
<td>6.01/7.49</td>
<td>9.13/8.46</td>
<td>13.28/9.26</td>
<td>0</td>
</tr>
<tr>
<td>Median</td>
<td>0</td>
<td>6</td>
<td>11</td>
<td>4</td>
<td>7</td>
<td>13</td>
<td>0</td>
</tr>
<tr>
<td>Mode</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Frequency distributions and CDF

The pedestrians’ waiting time distributions (Fig 25) further reveal the movement patterns of vehicles and pedestrians. The peaks of the extremely right-skewed distributions in Fig 25a and 25c show that most of the pedestrians
(risk-takers) crossed the intersection without waiting. While in cases of 50% likelihood of risk-taking behavior Fig 25b and 25d, the occurrences at longer waiting times show the successful negotiation by vehicles which improved the traffic flow.

![Figure 25](image)

(a) PHF-RA20  (b) PHF-RA50  (c) PHF-RA80  (d) PLF-RA20  (e) PLF-RA50  (f) PLF-RA80

Figure 25: Density graph for the waiting time data of pedestrians recorded in different experiment cases.

However, experiments with 80% risk-averse pedestrians reveal a random distribution of waiting times with few higher peaks around their waiting time limit of 20s (Fig 25c and 25f). The cumulative distribution graph for these waiting times is shown in Fig 26. The jump in CDF around 20s waiting time (Fig 26b) suggests the case of accumulation of risk-averse pedestrians for a long time which makes them impatient. This confirms the discussion on patterns observed in vehicles’ waiting time distributions where few vehicles have to wait much longer until the next negotiation opportunity. This shows that
negotiations allow the frequent release of traffic from both sides - vehicles and pedestrians, thus reducing the chances of congestion as compared to CM.

![Graphs showing cumulative distribution function (CDF) for waiting time of pedestrians in different experiment cases.]

(a) High pedestrian frequency (PHF)  
(b) Low pedestrian frequency (LHF)

Figure 26: Cumulative distribution function (CDF) graph for waiting time of pedestrians in different experiment cases.

### 6.4.3 Throughput analysis

The intersection throughputs for different experiment cases are presented in Table 15. In the NM, except for the case with fewer risk-averse pedestrians (PHF-RA20), in other cases, almost all the vehicles that were introduced in the simulation passed (throughput \( \approx 1200 \) veh/hour). For high pedestrian frequency and more risk-takers in the scene, the throughput in NM is reduced to 70%.

Table 15: Intersection throughput (vehicles/hour) for different experiment cases.

<table>
<thead>
<tr>
<th>PHF-RA20</th>
<th>PHF-RA50</th>
<th>PHF-RA80</th>
<th>CM-PHF</th>
<th>PLF-RA20</th>
<th>PLF-RA50</th>
<th>PLF-RA80</th>
<th>CM-PLF</th>
</tr>
</thead>
<tbody>
<tr>
<td>857</td>
<td>1189</td>
<td>1195</td>
<td>659</td>
<td>1180</td>
<td>1194</td>
<td>1195</td>
<td>1139</td>
</tr>
</tbody>
</table>

The NM performs better compared to the conservative model in which only 659 vehicles were able to pass (about 50% of the throughput in negotiation model). While in case of low pedestrian frequency the throughput for both models is the same and almost equal to the regular vehicle flow. It is clear then that more vehicles are passing through the intersection in the NM, which supports the hypothesis.

### 6.5 Conclusions

This work is build upon the previous models to allow vehicles to negotiate with multiple pedestrians considering also social rules in making individual decisions, without compromising pedestrians’ safety. It also includes different personalities in terms of risk-taking behavior, which are included in the social rules. Compared to the group
behavior in the previous model, this research demonstrates a more realistic scenario: negotiation by vehicles with a mix population of risk-averse and risk-taking pedestrians, every pedestrian taking own negotiation decisions. The model is realized through simulations using SUMO and MATLAB.

In the above experiments, the waiting time distributions for both vehicles and pedestrians give insights into the flow of traffic in both cases (negotiating v/s conservative behavior). Even with fewer risk-averse pedestrians, the traffic discharged frequently from both sides during negotiations, compared to a congested vehicle lane in the conservative model. Thus, risk-averse attitude of pedestrians increases the chances of vehicle to pass first which answers the research question for this chapter. In general, the simulation results show that negotiations reduce the waiting time for vehicles at intersections at the cost of some waiting time for pedestrians, resulting in a smooth flow of traffic. This supports the hypothesis of this study. Also, the waiting times for risk-averse pedestrians are not longer than their maximum waiting time limits observed in existing empirical studies.

However, the model presented here is subjected to a few constraints. The study so far was restricted to vehicles and pedestrians moving in a fixed and single direction, also the road design factors around intersections were not considered. Negotiations may be complex when there is an influence of traffic from other directions. The former issues are addressed in the next chapter.
This chapter is based on the conference paper “Scaling social rules to multi-party traffic negotiations” accepted in the Proceedings of the 26th ITS World Congress by Gupta, Vasardani, Lohani, and Winter (2019b). As such, most of the content in this chapter is compiled from this publication. My contribution as a first author in this work includes proposing the research problem and hypothesis; collecting the relevant information and performing analysis; evaluating the hypothesis; and also providing related discussions and conclusions. The entire work was supervised by my supervisor Prof Stephan Winter, and co-supervisor Dr Maria Vasardani, and external supervisor Prof Bharat Lohani, who actively provided their suggestions and feedback at each stage of this research.

7.1 INTRODUCTION

The negotiation concepts in the previous chapters were demonstrated only as a two-party interaction between a vehicle (with potential following vehicles) and pedestrians at an unmarked intersection. This chapter particularly aims to test the scalability of the negotiation model to a multi-party, multi-direction traffic scenario, i.e., vehicles approaching from multiple directions and of crossing paths, and pedestrian in multiple groups. It demonstrates its applicability to resolving right-of-way conflicts among these multiple parties, such that traffic throughput can be improved. The following research question from Section 1.3 is investigated in this chapter – Will social rules also improve the flow of multi-directional incoming traffic at intersections, while reducing the risk of collisions?

The concern of the previous studies was to demonstrate ways of improving the flow of traffic with negotiations between self-driving vehicles and pedestrians. With this ability being proven, social rules were introduced into the negotiation strategies involving individual decision making, also considering different risk-taking attitudes of pedestrians (Chapter 5 and Chapter 6). However, the interaction environment was restricted to pedestrian and vehicle traffic approaching each other from intersecting roads, disregarding traffic from other directions including vehicles intending to take a left or a right turn. The latter case introduces more right-of-way conflict problems. This research aims to investigate the applicability of those social rules to a more complex environment, i.e., also adding vehicles from other
directions intending to take a left turn through the same intersection. This becomes a multiparty negotiation problem and is presented here.

In the previous chapters, negotiation by social rules has shown significantly lower waiting times for vehicles compared to their conservative counterpart. The question addressed in this research is whether these social rules may also improve the flow of multi-directional incoming traffic at intersections, while reducing the risk of collisions. The hypothesis of this research is that compared to the vehicle’s conservative behavior, social rules of negotiations between connected vehicles and pedestrians approaching the intersections from different directions will improve the intersection throughput and their waiting times.

The methodology to realize the above goals is threefold: (a) scaling the environment complexity, (b) scaling the previous negotiation solution to this environment, and (c) analyzing negotiation’s impact on waiting times of vehicles. For this research again, the multi-party negotiation model is implemented using the SUMO and MATLAB toolboxes. The observables in this experiment are the waiting times of vehicles and the intersection throughput, analyzed for different frequencies of the pedestrian and vehicle flow. These parameters are then compared to the conservative behavior model in which vehicles are slowing down when sensing pedestrians intending to cross the road. The results show reduced waiting time for vehicles with negotiation, which also proves that the proposed concepts of negotiation are applicable to a multi-directional traffic scenario, given the vehicles are connected.

7.2 Theory

The negotiation problem between self-driving vehicles and pedestrians is defined as a process in which the two parties take steps to agree on who has the right of way to cross the conflict zone first. The previous work assumed the scenario of an unmarked intersection where pedestrians approach the road of the vehicle from an orthogonal direction. Traffic from other directions was not considered. This research work examines a more complex interaction scenario by adding traffic from other directions, making it now a multi-party conflict problem. The term party refers to the traffic from any direction, involving either pedestrians or vehicles. Considering traffic from different directions in a 4-way junction, the possible cases of non-conflicting movement of vehicles are represented in Fig 27. In general, the pedestrians can move in the direction(s) which does not conflict with the trajectories of moving vehicles. For example, in Fig 27a the pedestrians can move between points A and D. Similarly, in other cases (Fig 27b, Fig 27d, Fig 27e) the pedestrians can move between AB, DC, and BC respectively.
Figure 27: Multi-party traffic scenarios with non-conflicting movement of vehicles (in a right-hand traffic system).

Pedestrians can also move in non-conflicting directions in Fig 27c and Fig 27f. In the latter case, the vehicles can also take left turns while there are no trajectory conflicts with other vehicles, which is not shown in Fig 27f. While these parties move, the traffic from all other directions would, by social conventions and by traffic regulations demanding such social conventions, wait until they get a chance to pass. In all these cases, if any party wins the right of way then it also gives a chance to other non-conflicting parties to move at the same time. The major challenge in multi-party traffic negotiations is dealing with three different movements of traffic, i.e., movement conflict of straight going vehicles, vehicles crossing their direction, such as oncoming vehicles turning, or crossing vehicles, and pedestrians. The model proposed here is intended to be the simplest possible which captures the problem dynamics common to above cases, but which can also serve as a foundation for many more complex ones. Next, the negotiation process in a multi-party traffic scenario is discussed.
7.2.1 V2V negotiation

If there are no pedestrians trying to cross, then only the vehicles negotiate among themselves, which is the conventional case for connected and cooperative vehicles. To resolve the conflict at an intersection, conventionally the first-come-first-serve (FCFS) rule is used for collision-free movement of these vehicles (Tachet et al., 2016). Here, FCFS acts as a social rule which gives the right of way to the vehicle that approached the intersection’s starting edge first. If two vehicles approach an intersection at the same time, for example, if in Fig 29 both a straight-going and an oncoming left-turning vehicle reach the intersection at the same time, then the straight-going vehicle get the right of way, which is also a generally accepted social rule.

7.2.2 Negotiation workflow

The negotiation concepts are adapted from the previous conceptual model presented in Chapter 6 (Fig 15). The following negotiation process is further explained considering the current traffic complexity and how these negotiation concepts are applied to the multiparty conflict scenarios. The overall workflow is presented in Fig 28.

Negotiation between vehicles and pedestrians is required when there is a possible conflict in their trajectories. Note that vehicles follow ‘no overtaking’ policy in this work, so negotiation happens usually with the vehicles leading the queues. Each party’s trajectory can be extrapolated using their current position, speed, and heading parameters (Møgelmose, Trivedi, and Moeslund, 2015). Any pedestrian having a risk of collision with a vehicle from any direction, in principle, enters into a negotiation process with that vehicle.
### Social cues exchange

The model in Figure 15 shows the negotiation of any vehicle with the $i^{th}$ pedestrian at time instance $t$. Similar to the previous models, let us assume that any changes in the environment, including a pedestrian’s movement, gestures, and gaze, can be detected by the vehicle’s sensors using advanced machine learning technologies (Molchanov et al., 2015; Rasouli, Kotseruba, and Tsotsos, 2017). However, the model now applies to multiparty traffic scenario. The vehicle’s intention can be broadcasted as a common signal to all the competing pedestrians and other vehicles in the scene. This is assumed to be communicated to pedestrians via electronic channels such as text messages or light and sound indicators (Löcken et al., 2014), and among vehicles through V2V communication. The vehicle estimates these model parameters for every pedestrian in the scenario who is competing for the right of way. For connected vehicles, their motion parameters can be exchanged via V2V communication.

Based on perceived motion parameters of pedestrians, vehicles from all directions also estimate the risk of collision to the pedestrians, generally mapped in the range $[0, 1]$. The traffic situation at any time will be a mix of pedestrians who are at different degrees of risk. The vehicles, however, can only broadcast a common signal to the approaching pedestrians and other vehicles, so they wait for any further action until there are only high-risk pedestrians ($\text{risk} > 0.5$) near the curbside to negotiate with. In case there is a conflict with the vehicles from the other direction, they follow the FCFS principle. If the risk to the pedestrian with respect to any vehicle is high, then that vehicle tries to predict the intentions of the pedestrian. The possible cases are listed in Table 16 which are extended from the prior model discussed in Section 6.2.1. A more detailed method for risk-based negotiation with pedestrians is already explained in Chapter 6.

#### Seeking agreement

The vehicle estimates the pedestrian’s intention to yield based on the perceived pedestrian parameters such as gestures, gaze, and movement. However, as said earlier the discussion about intention estimation methods is not a part of this work. Having estimated the pedestrian’s intention, and using information from the connected vehicles from other directions, the vehicle tries to seek an overall agreement with the other conflicting parties (Fig 28). An agreement is reached when either (i) the pedestrian has indicated not to yield and other conflicting vehicles have indicated to slow down, or (ii) the pedestrian has indicated to one of the vehicles to yield, and vehicles resolve their right of way with FCFS agreement. This is presented in Fig 28. However, if both pedestrians and vehicles have conflicting intentions to cross first, then vehicles must negotiate with the pedestrians.
Table 16: Possible cases of risk to the pedestrians and corresponding action by the vehicle in that situation

<table>
<thead>
<tr>
<th>Pedestrian’s risk</th>
<th>Action by the vehicle</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \text{risk} = 0 )</td>
<td>no negotiation with pedestrian required, vehicle coordinates with other vehicles</td>
</tr>
<tr>
<td>( 0 &lt; \text{risk} &lt; 0.5 )</td>
<td>vehicle coordinates with other vehicles while monitoring pedestrian’s action</td>
</tr>
<tr>
<td>( \text{risk} \geq 0.5 )</td>
<td>negotiation with pedestrian as follows: (a) if (alert by vehicle) then vehicle follows FCFS policy (b) if (pedestrian is RA) then vehicle follows FCFS policy (c) if (pedestrian is RT) then vehicle slows down</td>
</tr>
</tbody>
</table>

7.2.2.3 Social rules and negotiation

In case there is no agreement, the vehicle with respect to which the pedestrians are at risk takes the opportunity to negotiate with them. Negotiation success, however, also depends on the risk-taking behavior of pedestrians (described in Chapter 6). They may be assertive and not yield, or may be too averse to take a risk. As discussed earlier, their behavior is also influenced by social rules and physical constraints. Social rules considered here are that pedestrians consider the queue length of waiting vehicles (\( > 3 \)) and physical constraints before taking a decision to cross. Again, their impatience and risk-taking behavior increase after 20 s of delay (Kaiser, 1994) and, thus, their willingness to cross increases. Any such behavior is reflected in their intentions. Based on their perceived behavior of pedestrians, vehicles prepare to slow down or speed up in the next step.

After this step, all parties indicate their intentions in the form of some signal and the negotiation cycle continues until an agreement is reached. At the next instance, there may be a change in the intentions of any party. For example, a pedestrian may acknowledge the vehicle’s right of way request by stopping, in which case an agreement is reached, and the vehicles from different directions cooperate among themselves for the right of way using FCFS policy. If there is no acknowledgment from either side, the negotiation cycle continues until an agreement is reached, while keeping safety constraints. Else, the vehicles prepare to slow down.
7.3 IMPLEMENTATION

To investigate this multi-party negotiation process, an implementation of the scenario presented in Fig 29 is presented. This multi-party scenario includes pedestrians (P), and vehicles from two directions: straight-going (SG), and oncoming but left-turning (LT). The environment considered is an unmarked intersection, where the different parties are approaching and only one party can cross safely the intersection at any given time. As before, it is also assumed that the vehicles have a vehicle-to-vehicle (V2V) communication channel to exchange information including each other’s motion parameters.

The proposed model is again simulated using SUMO and MATLAB and simulation is run for 24000 s (around seven hours) with a simulation timestep of 1 s each. An unmarked intersection is set up in SUMO as shown in Fig 30, where the length of the lane on which vehicle moves, from the start of the lane to the intersection, is 200m.

The pedestrian lane is meeting at the intersection, which is orthogonal to the vehicle lane. Again, the detection and perception of a pedestrian’s communication, such as gaze and gestures, cannot be modeled in SUMO so this process is not simulated. The vehicle and pedestrian behavior is modeled as a free flow. The left-turning ve-
Multi-party negotiations

Vehicles (LT) are introduced at the rate of 500 vehicles/hr from the left, while the straight going vehicles (SG) are introduced at the rate of 700 vehicles/hr from the right (Fig 30). The maximum intersection throughput is 1200 vehicles/hr. This flow is by default binomially distributed, approximating a Poisson distribution. The pedestrians are assumed to walk with an average walking speed of 1 m/s. Also, the waiting time limit for each pedestrian is randomly chosen from a normal distribution with mean waiting time of 20 s and standard deviation of 3.33 s. A binary value representing risk-taking or risk-averse behavior is randomly assigned to the pedestrian each with a probability of 50%. Two different frequencies of pedestrians are tested:

1. High frequency (HF), where a total of 4382 pedestrians are generated with a rate of appearance in the simulation between 1 s and 10 s.

2. Low frequency (LF), where a total of 2273 pedestrians are generated with a rate of appearance in the simulation between 1 s and 20 s.

The parameters recorded at each simulation step are speed and position of the vehicle and pedestrian, along with their respective distances from both lane center and curbside. The risk to each pedestrian in the scene is also computed at each simulation step. The interaction starts, and the negotiation workflow applies when the pedestrian’s risk becomes greater than zero.

The performance of the proposed negotiation model (NM) is compared to the conservative behavior model (CM) similar to the base model in the previous chapters. In the implementation of this model, the vehicle prepares to stop whenever a pedestrian is detected within 2 m from the curbside. The vehicle waits until all pedestrians have finished crossing and there is no other pedestrian detected nearby.

### 7.4 Results and Discussion

The observables in the simulation are the waiting times of pedestrians and vehicles at the intersection. Also, the total number of SG and LT vehicles which crossed the intersection at the end of the simulation are recorded to estimate the intersection throughput. The experiments are run for both negotiation and conservative models (NM and CM), for two different input frequencies of pedestrians (HF and LF).

#### 7.4.1 Average waiting time

The average waiting times of vehicles in different experiment cases are reported in Table 17. The average waiting time for both ST and
LT negotiating vehicles is about 200 s. The vehicle waiting time has increased compared to the two-party negotiation scenario in the previous model (Chapter 6), which was around 44 s, due to the increase in the number of competing parties in the negotiation. However, the waiting times are significantly less compared to the conservative vehicles. The conservative vehicles are delayed for more than 500 s when the pedestrian frequency was low. For high pedestrian frequency, the lane reached saturated congestion state and after 600 s of the simulation run, only a few vehicles were able to pass through. This occurred due to the short temporal gap between the arrival of pedestrians. Without any negotiation capabilities, the conservative vehicles didn’t find a gap in the pedestrian flow and hence they come to a standstill.

Table 17: Average waiting times of vehicles in different experiment cases

<table>
<thead>
<tr>
<th></th>
<th>SG-HF</th>
<th>LT-HF</th>
<th>SG-LF</th>
<th>LT-LF</th>
<th>SG-CM</th>
<th>LT-CM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>213.06 s</td>
<td>211.99 s</td>
<td>186.65 s</td>
<td>186.01 s</td>
<td>507.81 s</td>
<td>504.61 s</td>
</tr>
<tr>
<td>SD</td>
<td>25.11 s</td>
<td>23.83 s</td>
<td>22.56 s</td>
<td>21.25 s</td>
<td>87.74 s</td>
<td>80.48 s</td>
</tr>
</tbody>
</table>

The waiting time distribution for vehicles and pedestrians is shown in Fig 31 and 32 respectively. Clearly, the waiting times for most of the conservative vehicles are significantly more compared to negotiating vehicles. While most of the negotiating vehicles are delayed by less than 250s, the conservative vehicles are delayed for more than 500s.

Figure 31: Waiting times distribution for vehicles in Negotiation model (NM) and Conservative model (CM) for high pedestrian frequency.
On the other hand, the average pedestrian waiting times are less than 20s, but a few pedestrians have waiting times up to 30s. As discussed in the previous chapter, the longer waiting pedestrians belong to the risk-averse category who follow social norms and allow the waiting vehicles to pass first. Nevertheless, the pedestrian waiting times fall within the acceptable average waiting time limits for pedestrians (Li, 2014), and is less than 20 s (SD = 8.96s) in both experiments. The pedestrians’ waiting time allows other negotiating parties (vehicles) to clear their queues. Also, the FCFS policy among vehicles makes it possible to remove a few long waiting vehicles from the waiting queue.

7.4.2 Frequency distribution of waiting times

The frequency distribution of waiting times of vehicles is presented in Table 18. More than 90% of both SG and LT vehicles experienced delays between 180 s - 240 s, while most of the conservative vehicles were delayed for more than 300 s. The latter indicates severe congestion problems during peak hours of vehicular and pedestrians traffic.

Existing studies in the literature have reported that waiting times above 90 s at a single intersection increase the risk-taking behavior among human drivers (Bijl et al., 2011). On contrary, studies have also proved drivers’ acceptance for up to 4 min (240 s) of ramp delay combined with increasing freeway travel speed (Levinson et al., 2006). Similar waiting tolerance of drivers has been observed at level crossings as well (Larue, Blackman, and Freeman, 2018). This means
Table 18: Frequency distribution of waiting times of vehicles in different experiment cases

<table>
<thead>
<tr>
<th></th>
<th>30 s</th>
<th>60 s</th>
<th>120 s</th>
<th>180 s</th>
<th>240 s</th>
<th>300 s</th>
<th>&gt;300 s</th>
</tr>
</thead>
<tbody>
<tr>
<td>SG-HF</td>
<td>0.17%</td>
<td>0.38%</td>
<td>0.64%</td>
<td>4.39%</td>
<td>86.65%</td>
<td>7.74%</td>
<td>0%</td>
</tr>
<tr>
<td>LT-HF</td>
<td>0.13%</td>
<td>0.22%</td>
<td>0.56%</td>
<td>5.71%</td>
<td>86.38%</td>
<td>7.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>SG-LF</td>
<td>0.23%</td>
<td>0.43%</td>
<td>0.93%</td>
<td>31.94%</td>
<td>65.51%</td>
<td>0.97%</td>
<td>0.00%</td>
</tr>
<tr>
<td>LT-LF</td>
<td>0.16%</td>
<td>0.35%</td>
<td>0.62%</td>
<td>35.23%</td>
<td>62.67%</td>
<td>0.97%</td>
<td>0.00%</td>
</tr>
<tr>
<td>SG-CM</td>
<td>0.27%</td>
<td>0.18%</td>
<td>0.73%</td>
<td>0.54%</td>
<td>0.64%</td>
<td>0.36%</td>
<td>97.25%</td>
</tr>
<tr>
<td>LT-CM</td>
<td>0.27%</td>
<td>0.09%</td>
<td>0.46%</td>
<td>0.37%</td>
<td>0.55%</td>
<td>0.18%</td>
<td>98.05%</td>
</tr>
</tbody>
</table>

that conservative behavior of vehicles will be quite frustrating for the passengers, while negotiation is able to improve these waiting times within waiting tolerance limits, while also keeping the pedestrians safe.

7.5 conclusions

This research supported the applicability of the previous model of negotiation for self-driving vehicles and pedestrians to more complex and realistic scenarios. The right-of-way conflict was considered between pedestrians, straight going and left turning vehicles and a demo study was implemented using SUMO and MATLAB. Negotiation between these parties is demonstrated using concepts from the previous model. This study shows the scalability of social rules to
multiparty traffic negotiation and overall improvement in the traffic flow at intersections.

The results also prove that negotiations will reduce the waiting time for vehicles and improve the overall throughput at intersections even in complex traffic scenarios, compared to vehicles’ conservative behavior. However, the study also revealed that compared to previous studies, these waiting times have increased in multi-party scenarios due to competition among more parties intending to get the right of way. On the other hand, the pedestrians’ waiting times depend on their risk-taking behavior, and do not exceed their impatience limit.
DISCUSSION

This chapter provides a discussion of major results from the experiments along with the limitations of the analysis in this work. Firstly, a cost-benefit analysis of negotiations is provided based on the major results of this thesis. This is followed by a discussion of potential challenges indicated by this research which are not yet solved. This chapter concludes by providing an evaluation of the overall hypothesis of this research.

8.1 cost-benefit analysis

The costs and the benefits of the negotiation model can be discussed in terms of the social, economic, and environmental impacts of the negotiations.

social impact
As demonstrated in Chapters 4, 5, 6, and 7, negotiation increases the throughput for vehicles as compared to the slower conservative vehicles by providing them better chances to pass through a continuous flow of pedestrians competing for road space. The reduced waiting times and smoother speed profiles for vehicles reduce the chances of congestion on the roads. As there is no delay for pedestrians in the conservative model, the benefits to the negotiating vehicles come at the cost of some waiting time for pedestrians. However, the simulation results show that the pedestrians’ waiting time (13s in the worst case) is much less than the waiting times for a large number of conservative vehicles (> 600s), and also relatively short compared to the average waiting times at traffic-light regulated intersections. Hence, the waiting times of pedestrians are socially acceptable (Li, 2013, 2014).

ECONOMIC IMPACT
Both waiting times and smoother speed profiles can also be expressed as economic utility. For example, simulations of the conservative model demonstrate that the 'stop-and-go' behavior when encountering a pedestrian impacts also a number of the following vehicles as well. Negotiation improves the speed profile of negotiating vehicles as well as the following vehicles, and allows them to run smoothly on the road, thus consuming less fuel as compared to conservative vehicles (Alessandrini et al., 2012). Also, sudden breaks causing stronger wear and tear of tires and road surfaces can be reduced by improved traffic flow (Stalnaker et al., 1996).
ENVIRONMENTAL IMPACT

There is also an indirect impact on the surroundings of the intersections. Smoother running traffic not only consumes less fuel, but also produces lower CO\textsubscript{2} and particle emissions in the environment (Alessandrin et al., 2012) – one harmful to the climate, the other harmful especially to the pedestrians. Thus, the consequent benefits of negotiation are a more liveable environment and a reduced risk of health hazards. Should, in the future, self-driving cars be equipped with electrical powertrains, the environmental benefit will depend on the way the electrical power is generated, and the wear and tear of batteries.

8.2 MAJOR DISCUSSIONS AND LIMITATIONS

The following section analyses the potential challenges and limitations associated with this work.

8.2.1 Cultural variations in language of traffic

The interpretation of pedestrians’ gestures is a crucial factor for negotiations by self-driving vehicles. Chapter 3 concludes that traffic controllers’ hand signals for the same commands vary across different countries, and hence are not universal. The study in this research is restricted to regulated codes of traffic control. In a broader sense, the above results further raises other concerns related to cultural variations in the language of traffic. However, the above results also show that all gestures have a base in affordance. Thus, future work in this direction can extend the study to people’s interpretation of these gestures - it is possible that people understand gestures even across cultures or traffic codes due to their affordance.

Another open question is whether any of these agreed (codified) gestures are also used by pedestrians and human vehicle drivers, for example to negotiate their right of way. Even future vehicles can be enabled to learn affordances in road users’ gestures, to perceive different traffic gestures across cultures and their associated meanings. Additionally, the contextual knowledge of certain situations, e.g. during a negotiation, along with gesture interpretation may allow them to anticipate the intentions of various human users on roads. Ultimately, self-driving vehicles need to understand the intentions of other road users exhibiting the language of gestural interaction.

8.2.2 Simulation constraints

Simulation was used to forecast the performance of the proposed negotiation model. One of the most challenging aspect of this thesis is relating the traffic modelling to real-world scenarios. The func-
tional safety of any automated vehicle is an important part of design (Schöner, 2018), i.e. the self-driving vehicle software should be able to handle any type of situation on road. However, the simulation test bed in this thesis does not guarantee that every type of vehicle-pedestrian encounters are captured and tested in the experiments. For example, jaywalking behavior of pedestrians is not included in the current experiments, and similarly it was difficult to simulate their interaction with non verbal cues. Rather, these cues were mapped to probabilistic numbers for inclusion in the simulations.

For the development and testing of any models related to self-driving vehicles, thorough verification and validation procedures are required. Practically, these tests can only be performed in the field or in special testing sites. But the limited availability of self-driving vehicle prototypes makes it difficult to validate the model for real traffic applications. In this context, several research groups are working on other ways to create autonomous vehicle testbed. Their interaction studies involve virtual-reality based simulation testbeds or driving current level 3 vehicles with a ghost driver, and pilot studies to test various external human-machine interfaces (see more details in Section 2.2.1 and 2.2.2). However, these methods have limited applications depending on the level of research. Also, these methods often induce a bias in testing as the human subjects involved in the study don't perceive the same risk as they do in real-life situations.

Though this research validates the scalability of negotiations to multi-party traffic scenarios, yet there are a few assumptions and limitations. Currently, it is assumed that a vehicle from any direction is moving in a single lane, in a fixed direction, with no option to change lane at any time (except the left turning operation of the vehicle in multiparty negotiations in Chapter 7). The road design factors around intersections are also not considered in this work. Future work in this direction can consider environmental constraints and more complex negotiation scenarios such as vehicles’ lane merging operations or pedestrians suddenly changing their movement direction. On similar grounds, the work could be expanded to mimic the actual negotiation happening on roads.

8.2.3 Pedestrian behavioral risks

Current simulations capture different pedestrians’ risk-taking crossing behaviors at a macroscopic level. However, the model and its simulation has a few limitations, especially when dealing with the unpredictability of pedestrian behavior in real-life situations. Some road users can more easily change their behavior at the last minute. From the pedestrians’ point of view, there may be concern regarding the perception or comprehension of future vehicle’s intentions. Also, the above results may vary in real-life settings as it is difficult to de-
termine the road users’ accurate behavior in any situation. The above results can be further tested with better pedestrian behavior models (Helbing and Molnar, 1995; Johansson, Helbing, and Shukla, 2007; Ma et al., 2010), demonstrating their characteristics at microscopic level. However even these theoretical behavioral models do not fully capture the complex behavior of humans.

Besides the above issues, the negotiations by vehicles will also rely on the robustness of pedestrian’s intention estimation methods. For example, jaywalking is common among pedestrians and will confuse the future vehicles about pedestrian’s intentions. If future vehicles can learn such behaviors and be able to detect them, then they can act accordingly. The proposed model assumes intention estimation probabilities in terms of pedestrians’ chances of yielding and not yielding and uses that estimate to compute its motion strategy. However, the effect of a false positive behavior estimation is not considered in this work. The former case may cause the vehicle to wrongly proceed, which increases the risk of collision. The frequency of such cases will depend on how often the artificial intelligence models correctly predict the motion of pedestrians. Arguably, the performance of vehicles’ vision models should be looked at more closely to eliminate such errors before the deployment of these vehicles on roads. Accuracy in comprehension of the other party’s behavior also matters. These concerns are indirectly related to a major question – whether artificial intelligence in future vehicles is capable of capturing the complex behavior of humans, and if so then to what extent.

8.2.4 Ensuring an agreement

The key component of the proposed model is ensuring an agreement during negotiation and the level of commitment to a given behavior matters in an agreement. The proposed model assumes that the vehicle is continuously tracking the action of pedestrians which incorporates any changes in pedestrian’s behavior in the next negotiation cycle. However, the above results are limited by simulated pedestrian behaviors. Not surprisingly, in some actual road situations the vehicle may encounter unexpected changes in pedestrian’s behavior. Such unexpected and negligent pedestrian behaviors may happen in sub seconds time interval which is currently not captured in the simulations. The negotiation model can be further made more reliable with sub-seconds intervals of interaction. For example, if the timestamp is changed to 0.5s then the vehicle can better capture quick changes in the behavior of pedestrians and include that in its negotiation strategy. A finer interaction interval would benefit the vehicle to capture any unexpected changes in pedestrian’s agreed behavior during an agreement.

---

1 In simulations, the negotiation cycle is set to 1s as the accepted simulation time-step value in SUMO is an integer value in seconds.
agreement. This would also mean that the risk of taking a wrong decision by vehicle will also reduce as the vehicle’s motion strategy can be planned on a finer scale. Since this modification (and further decreasing time intervals) would improve the quality of the engagement but does not change the model of engagement it can be left for future work that also considers the computational load on vehicles in estimating pedestrian intentions.

So, minimizing the negotiation cycle interval will be a challenge while designing self-driving vehicle’s software. Also, it will be crucial in the design of future vehicles that they are able to correctly estimate the degree of likelihood that a pedestrian will suddenly change an agreed action. Moreover, the vehicles should also be programmed for best possible preventive measures in such situations.

8.3 Evaluation of Overall Hypothesis

As pointed out in the game theoretical analysis by Millard-Ball (2018), most of the times pedestrians would seize the opportunity to cross before self-driving vehicles making vehicles a much slower participant in the traffic. The simulation results, considering different approaches and test scenarios, confirms the overall hypothesis of this research - in future, negotiations can reduce the average waiting time of self-driving vehicles and improve the overall throughput at intersections, compared to their conservative behavior.

A summary of overall results from different models presented in this thesis is listed in Table 19. Chapter 4 demonstrated a simple scenario of one-to-one negotiation in less congested traffic scenario and there was not much difference in the traffic throughput from two models. As the complexity increased to more frequent vehicle-pedestrian interaction scenarios (Chapters 5–7), the negotiation model showed better performance in reducing vehicles’ waiting times and traffic throughput. The results also reflect that the average waiting times for vehicles increase when there are more competing parties (Chapter 7), but the pedestrian waiting times do not exceed their maximum limits (Li, 2014). Furthermore, the adverse impacts of the conservative behavior of vehicles on the overall flow of traffic (causing lane congestion) further validates the above hypothesis.

The above results however largely depend on pedestrians’ behaviors. All the models described in this thesis assume that a certain action by the pedestrian clearly reflects their action to yield or not yield in the next few seconds. However, few actions of pedestrians may be unpredictable, for example, a pedestrian busy looking at their smartphone while walking near the curbside. A better insights into pedestrian behaviors would do the essential improvements in the model and results, yet for this research hypothesis it is reasonable to categorise pedestrians’ behaviors at crossings as either of the following
Table 19: Summary of performance for different models. WT denotes average waiting time

<table>
<thead>
<tr>
<th>Model</th>
<th>Negotiating vehicles</th>
<th>Conservative vehicles</th>
<th>Pedestrians</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>One-to-one negotiation</strong></td>
<td>WT: 11.8 s</td>
<td>WT: 44 s</td>
<td>WT &lt;20 s</td>
</tr>
<tr>
<td></td>
<td>Throughput: ~100%</td>
<td>Throughput: ~100%</td>
<td></td>
</tr>
<tr>
<td><strong>Social rules</strong></td>
<td>WT: &lt;15 s</td>
<td>WT: &gt;100 s</td>
<td>WT &lt;20 s</td>
</tr>
<tr>
<td></td>
<td>Throughput: 98%</td>
<td>Throughput: 50%,</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>worst case 12%</td>
<td></td>
</tr>
<tr>
<td><strong>Risk-based model</strong></td>
<td>WT: 44.5 s</td>
<td>WT: &gt;100 s</td>
<td>WT &lt;20 s</td>
</tr>
<tr>
<td></td>
<td>Throughput: 98%,</td>
<td>Throughput: 50%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>worst case: 72%</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Multi-party negotiations</strong></td>
<td>WT: 180 s - 240 s</td>
<td>WT: &gt;500 s</td>
<td>WT &lt;20 s</td>
</tr>
<tr>
<td></td>
<td>Throughput: 65%</td>
<td>Throughput: 27%,</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>saturated congestion</td>
<td></td>
</tr>
</tbody>
</table>

two types - the ones willing to yield to the vehicles, \textit{i.e.} risk-averse, and the other ones who assert their right of way \textit{i.e.} risk-takers. It is known that not every pedestrian is same in terms of their road crossing behavior – some might show less alertness in traffic compared to others which leads to their risky behaviors on roads. Moreover, any pedestrian’s behavior depends on their individual cognitive abilities to perceive risk, besides individual characteristics their behavior can be influenced by some social factors. This research captures those factors and different pedestrian behaviors while evaluating the above hypothesis, and thus the above results hold true to show the effectiveness of the proposed model.

These results are subjected to few simulation constraints as discussed before, yet this thesis is able to demonstrate possible directions for innovations in future human-vehicle interactions. As said in this thesis, instead of yielding to the approaching pedestrian, future self-driving vehicles can increase their chances of passing the crossing point first with negotiations. This would lead to the strategic advantage of having a smoothly running traffic in future along with a better coordination among various road participants.

The vision of this thesis is to ensure that there is an optimum level of pedestrian trust that makes pedestrians feel comfortable to cross the roads while reducing pedestrians’ risky, inattentive and aggressive behavior to avoid unnecessary delays to future vehicles. The broader contribution of this thesis is to highlight the opportunities of fair negotiations to overcome the undesirable consequences of pedestrians always having the preference. Here, the pedestrian’s compliance with the fair negotiation theory can be weighed with the
strategic incentives it brings to them. The most relevant advantage to pedestrians is maintaining their situational awareness, which may diminish if conservative self-driving vehicles will be on roads. Not only awareness but the fact that these vehicles engage (in contrast to react) may contribute to trust and useability of future vehicles. The other aspect is pedestrians’ tendency to social conformity – pedestrians are social in nature; they largely adhere to social norms and adapt their behaviors to new situations. For example, anyone as a tourist (as a driver or a pedestrian) has experienced for themselves a change in culturally embedded social rules and local behaviors in traffic. Despite of initial confusion and irritation, local traffic culture is unconsciously adapted over time. Similarly, it can be expected that pedestrians will shape their perception and attitude towards future vehicles to make the most of self-driving vehicles’ advantages and avoid the disadvantages, which will also develop their negotiating behavior with vehicles.

This chapter highlighted the limitations of the work presented in this thesis and provided an evaluation of the overall hypothesis of this research. The next, and the last chapter of this thesis provides concluding remarks and future research directions. These future directions are build on the limitations of this research identified in this chapter.
CONCLUDING REMARKS AND FUTURE DIRECTIONS

Looking into the future of self-driving vehicle’s engagement with other road users, as initiated in this thesis, there are yet many challenges to make it a reality in the future. This chapter outlines the general implications of this research, and concludes with recommendations for future research directions.

9.1 CONTRIBUTIONS OF THIS THESIS

Existing studies concerning the interaction of vehicles and pedestrians are limited to human behavioral psychology, to algorithms for the pedestrian intention recognition, and empirical research to understand pedestrians’ trust towards future self-driving vehicles. This research, however, is an attempt to describe another aspect of traffic behavior – right-of-way negotiations among self-driving vehicles and pedestrians. The aim of the research is a more natural interaction of a self-driving vehicle with the intentions and behaviours of pedestrians, and thus make the road cohabitation of people and machines (here vehicles) less stressful for people. Also, we argue that a more natural behaviour of the robotic vehicle (in the eyes of the pedestrian) also leads to gains in throughput. As such, this thesis proposes a vehicle-pedestrian negotiation framework realized in three stages of conceptualization. To our knowledge, the proposed negotiation model(s) for decision making in traffic is novel.

The highlights of this thesis are an investigation into gestures in traffic, three vehicle-pedestrian negotiation frameworks, concluded with a study on scalability and validation of the model in multi-party traffic scenarios as listed below:

1. Universality of gestures (Chapter 3): This thesis first studied the traffic controllers’ hand signal rules to investigate whether there are universal gestures to interact in traffic. The identified differences in regulated codes confirm non-universality of gestures in traffic, but a further exploration reveals their common base through affordance. This study, hence, provides a motivation to look into an affordance-based vehicle control system. Also, the findings of this study reveal various elements involved in a gesture which in future have to be understood by a self-driving vehicle (especially during negotiations).
2. **Negotiation framework** (Chapter 4): To start with, a proof of concept for negotiation model is established first. In the first stage of research, negotiation between a single vehicle and a single pedestrian at a time is modeled based on physical constraints between them. The results of reduced waiting times of vehicles with negotiations lays the foundation for further research in the topic.

3. **Social rules in negotiation** (Chapter 5): To further investigate decision-making among multiple pedestrians and vehicles, a revised model is proposed introducing social rules to replicate informal social norms followed by traffic participants in everyday traffic interactions. However, the rules are applicable only to groups of pedestrians and vehicles. This kind of negotiation strategy demonstrated reduced the conflict of interests among groups of pedestrians and vehicles, and a balanced flow of traffic.

4. **Pedestrian’s risk-based negotiation model** (Chapter 6): To address the previous group constraint the model is further extended introducing pedestrians’ individual decision-making while also following the social rules, along with a consideration of their different risk-taking attitudes towards vehicles. This model demonstrated the potential of negotiations to reduce vehicles’ waiting times while confronting a mix-population of pedestrians at the intersections.

5. **Scalability validation** (Chapter 7): The last stage of this thesis involved scaling social rules to multi-party negotiations. The objective is to validate the scalability of the revised model presented in Chapter 6 to multi-party traffic scenarios. The results validate the applicability of proposed negotiation concepts to more complex scenarios and also confirms the overall hypothesis of this research as discussed in Chapter 8.

The simulation results confirm the effectiveness of the negotiation model in improving the waiting times of vehicles and the intersection throughput. This thesis demonstrates that future self-driving vehicles will be slowed down significantly if they are programmed to be conservative towards pedestrians. Overall, the research emphasizes that there is a need to engage future self-driving vehicles in interaction with other road users to maintain the flow of traffic. The findings from this research demonstrate the positive impact of those interactions on traffic throughput, but also highlights the challenges to realize the goal of replicating human-like decision making in self-driving vehicles. Few of these challenges related to this work are outlined in Chapter 8. The implications along with associated challenges of this research can be further exploited to address wider issues in this
domain, a few of them are discussed next in the last section of this thesis.

9.2 Future Directions

This thesis concludes by listing a few directions where this research can further help in improving the decision making of self-driving vehicles to ultimately make them capable of sharing the roads with humans.

Affordance-based Vehicle Control System

The work in Chapter 3 identifies that gestures in traffic vary across cultures, which further motivates to look into people’s interpretation of traffic gestures across cultures due to affordances identified in traffic codes. Similarly, affordance can also enable a vehicle to perceive signals of pedestrians in relation to kinematic characteristics of pedestrians’ gestures. Further work is required to confirm this hypothesis. A perception and action model for the vehicle is feasible but the challenge here lies in identifying the close-to-truth match across multiple affordances possible for a given gesture. This type of vehicle model recognizing the generalised meaning of different traffic gestures is important to resolve intention conflicts, especially during negotiations. This way pedestrian can also develop their behavior to engage in two-way communication with future vehicles knowing that the vehicle can recognize and respond to their actions. Research on affordance learning for autonomous driving is gaining attention (Marti, Morice, and Montagne, 2015; Ryu et al., 2016), and future work can also look into ways of incorporating the representations and meanings of various traffic gestures as well.

Communication Channels

Closely related to the question of gesture interpretations is the issue of communicating intent of vehicles, and more importantly ensuring that the message is delivered to the pedestrian in the correct context. The negotiation model in this thesis works on the underlying assumption of a clear communication channel to communicate intent among vehicles and pedestrians. However, reaching that level of communication technology is still a challenge. The industrial solutions discussed in Chapter 2 are limited in their functionality due to a variety of reasons. Firstly, pedestrians have limited ability to assess the visual indicators (such as text messages on windshields) in vehicle especially due to their motion and large distance. Similarly, robotic gestures and gaze installed in vehicle can only be recognised during slow motion of the vehicles. In contrast, the audio and light
indicators can attract pedestrian’s attention, but then assuring a feedback from pedestrians is time-critical in this case. This is an ongoing area of research and future work can look into combining V2P technologies with other communication modalities to mitigate the current issues.

BEHAVIOR PREDICTION MODELS

Pedestrian intention estimation is central to the proposed model for vehicles presented in this thesis. During an anticipated crossing conflict with pedestrians, it is necessary for the vehicle to understand pedestrians’ intentions and respond within safe time limits. The vehicle can encounter any situation – in an ideal case, vehicle can confidently recognize a pedestrian’s intention based on their head looking one direction. However, in other situations there can be perceivable risks in believing the vehicle’s machine learning models when the pedestrians are negligent to social rules, for example situations where pedestrians are engaged with their smartphones near crossing areas, or inadvertent children suddenly coming in the path of vehicle. The latter situations have been not considered in the proposed model.

Enabling future vehicles to learn all kinds of predictable and irrational behaviour of pedestrians is still a major challenge for the automakers. This is evident from the recent incident of Uber hitting a pedestrian at Arizona. The incident report by the National Transportation Safety Board (US) outlined the main cause of accident as follows: “the self-driving system software classified the pedestrian as an unknown object and the vehicle operator intervened less than a second before the impact (pp. 2)” (NTSB, 2018). This limitation of current technology is also crucial in context of enabling negotiations in future vehicles. As such, future autonomous vehicle behavior prediction models have to essentially deal with the following challenges – (1) near prediction of all kinds of human behavior within the scope of the safe response times; (2) evaluating and reducing the risk of predicting false positives (and negatives) in the machine learning models; (3) furthermore, for dynamic decision-making the system has to deal with the computational complexity involved in comprehending vehicle’s surroundings every sub-seconds of driving.

VARIETY OF SOCIAL BEHAVIORS AND NORMS

Besides identifying the normal road behaviors, self-driving vehicle needs to learn everyday social behaviors as well. This thesis presented a few social rules among vehicles and pedestrians to demonstrate ne-
9.2 Future Directions

Gotiations, however not every type of social behavior and rules is covered in this thesis. The factors such as place of interaction and situation context are not considered in the current model. For example, the social rules of driving are different at busy city centers compared to a highway, in the former case pedestrians are expected to ignore the rules more often and drivers expect to drive slow around pedestrians as a general accepted rule. Another example of context-based behavior is: a pedestrian waiting at the road side near parking space may not necessarily intend to cross the road, but may be waiting for their vehicle to arrive. In this case, drivers are already aware of these kind of intentions which they have learned through experience. But self-driving vehicles lack such capabilities to identify situation dependent road users’ behaviors. The context of the situation also plays a major role in learning road behaviors – the amount of traffic flow, time of the day, type of place, cultural norms of a place, etc.

In particular, these social norms vary widely among cultures. As such, a universal rule database of social norms is difficult to program into the behavior of vehicles. The probable future research direction is to look into methods to make the self-driving vehicles learn these social rules, possibly the country-specific behaviors. Current trials of different vehicle prototypes aim to improve their perception of different behavior through experiences, i.e. training their machine-learning models with real-situation data. Yet the concern is: Is learning by experience enough to ensure that the vehicle can interpret all types of road behaviors and social rules?

Connected Public Transport and Emergency Vehicles

The other aspect of road scenarios that this thesis does not cover is the presence of public transport. The question is whether social rules will be different in their presence. Negotiations can be studied further by considering pedestrian’s crossing strategy against heavy duty vehicles. Another interesting question is how well will self-driving vehicle handle awareness of the vehicles with special rights, such as emergency vehicles and police patrolling vehicles. In case of any emergency, drivers are required to get out of the way of any ambulance, police vehicle, or fire brigade. However, in few circumstances it may not be safe for the driver or self-driving vehicles to give way to emergency vehicles. The vehicle might be stopped at red light when it detects the emergency siren, or a pedestrian might be crossing at that time and it is not safe to pull over the vehicle. In many situations, road users cooperate among themselves to facilitate a safe passage for the emergency vehicles. The self-organisation among connected vehicles to give way to emergency vehicles is possible in future, however when pedestrians are also involved then cooperation becomes challenging. Also, it is not clear how the presence of emergency vehicles
among self-driving vehicles affect the flow of traffic. This opens up a new perspective of negotiation problem when emergency vehicles are also involved. Future work can investigate the psychological factors involved in the road users’ response to emergency vehicles, and also research into the acceptable behavior of future vehicles in any emergency situations.

The benefits of improved safety and transport efficiency with automated and connected vehicles can only be leveraged when the vehicles can take dynamic decisions in presence of humans – as this thesis has demonstrated. Yet it will take a few years to shape the socially acceptable behavior of self-driving vehicles; even if they are deployed earlier they have to continuously update their perception of the environment.


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Title: Negotiations between self-driving vehicles and pedestrians for the rights of way at unmarked intersections

Date: 2019

Persistent Link: http://hdl.handle.net/11343/234422

File Description: Final thesis file

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